May 2015

Spatial Features of Labor Markets and Links to the Housing Market

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ABSTRACT

This dissertation comprises three papers on spatial features of labor markets and links to the housing market. The first two papers look at how a local parental leave policy and the neighborhood in which one resides can influence women's decision to work. One paper shows that New Jersey's 2009 family leave insurance program induces women to remain employed following childbirth. The other reveals that, for women, having other women with similar aged children to yours among your closest neighbors makes you emulate their work behavior. The final paper analyzes how seasonality in occupational employment via either monthly or business-cycle induced fluctuations to labor demand increases the likelihood of holding a home equity line of credit. This finding is consistent with individuals drawing on these credit lines to access stored home equity in order to smooth consumption in the face of short-term breaks to employment.

SPATIAL FEATURES OF LABOR MARKETS AND LINKS
TO THE HOUSING MARKET

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DISSERTATION

Submitted in fulfillment of the requirements for the
degree of Doctor of Philosophy in Economics in
the Graduate School of Syracuse University

May 2015

ACKNOWLEDGEMENTS

I want to express my gratitude to my advisor Stuart Rosenthal for his invaluable assistance and guidance throughout. I am also thankful to Alfonso Flores-Lagunes, Sarah Hamersma, William Horrace, Jeffrey Kubik, Yoonseok Lee, Jan Ondrich, Eleonora Patacchini, and dissertation workshop and department seminar participants for their helpful comments and suggestions. Finally, I thank my parents Ana and Rui, my brothers Francisco and Pedro, my grandparents, and my wife Judie; without whose support completion of this dissertation would not have been possible.

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Chapter 1

Spatial Features of Labor Markets and Links to the Housing Market

The overarching theme of this dissertation is that spatial features of labor markets and in particular their links to what is happening in the housing market impact individuals' labor market outcomes. Two of the papers, presented in chapters 2 and 3, analyze how such spatial features impact women's decision to work. One looks at how a state-specific parental leave policy can impact women's decision to remain in the labor force following childbirth. The other directly ties the conditions in women's residential neighborhood to their work decision, via the influence of neighboring peers. The third paper, in chapter 4, further highlights the link between the housing market and labor market outcomes by showing how individuals can draw upon stored home equity when facing uncertainty in employment.

Childbearing and rearing contribute to women experiencing greater working career interruptions than men, impacting future employment outcomes. The paper in the second chapter uses New Jersey's 2009 mandate requiring firms to provide workers paid leave during their child's first year of life to assess how it affects subsequent employment. A spatial differencing method is carried out using American Community Survey from 2005 to 2012. The method compares difference-in-differences estimates of how the policy impacts potentially eligible women's employment in New Jersey to those same estimates for women living further away from New Jersey. A woman is deemed potentially eligible if she had a child in 2009 or later. This differencing strategy allied to the use of state by year fixed effects seeks to capture heterogeneity in local economic conditions that may bias estimated policy impacts. I find the policy increases married women's employment probability by approximately 3 percentage points in the year of potential leave take-up and this effect persists in the three subsequent years. No significant policy effects on employment are found for men or single women.

The third chapter is joint work with Eleonora Patacchini and Stuart Rosenthal. This paper examines the influence of neighborhood peer effects on the decision of women to work using 1985-1993 American Housing Survey data that follows clusters of adjacent homes over time. Modeling assumptions imply rank order restrictions on the effect of nearby working and non-working peers and non-peers that guide the analysis. Estimates indicate that female labor supply is sensitive to peer effects and at least in part because women emulate the work behavior of nearby women with similar age children. For men, peer effects are present in simply specified models but disappear in more robust specifications, consistent with inelastic work decisions. Findings confirm the value of geographically concentrated panel data and other modeling features when attempting to identify peer effects.

The last paper analyzes how the frequency and predictability of facing spells of unemployment impacts households' demand for home equity loans or lines of credit (HELOC). These devices represent a low transactions cost way of extracting stored home equity. Using American Community Survey 2003-2013 data, I find working age household heads whose occupational unemployment rates are significantly impacted by changes in GDP, or business cycle effects, are more likely to secure access to a HELOC. Estimated effects are strongest for younger individuals. For this group facing monthly seasonality in employment further increases their tendency to hold a HELOC. Evidence of these impacts on younger households' probability of holding a HELOC is most robust when coupled with house price appreciation that likely lifts credit supply restrictions they may face. Results are consistent with consumption smoothing motives impacting the demand for HELOCs.

Chapter 2

Local Parental Leave Assistance and Long-Term Effects on Female Labor Supply

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2.1 Introduction

Previous research has found that temporary breaks from the labor force contribute to worse labor market outcomes later in life (e.g. Blau and Kahn, 1997, 2006; and Kim and Polachek, 1994). One such break in employment occurs for women who decide to drop out of the labor force during childbearing years. This paper makes use of the enaction of a paid leave policy in New Jersey in 2009 that directly reduces the likelihood of such a break occurring to assess its impact on women's employment probabilities in the years following childbirth.

Using American Community Survey data from 2005 to 2012, I employ a spatial differencing strategy consisting of two steps. First, difference-in-differences estimates of the paid leave policy's impact on the employment probability of women potentially eligible for the policy is computed for different geographic areas. Mothers are potentially eligible if they had a child born in 2009 or later. In these regressions, women with no child or whose child was born before the policy was enacted are the control group. In the second step, estimated impacts for potentially eligible women in the New Jersey sample are compared to those for samples at various distances from New Jersey. This differencing across geographic areas as well as the use of state by year fixed effects in estimating regressions enables a more precise identification of policy impacts.

Given this estimation strategy, the most credible estimate of the paid leave policy's impact on employment shows a 3.1 percentage point increase in the employment probability of married women in the year they are potentially eligible to receive paid leave benefits. Furthermore, estimates show this increase in employment relative to policy-ineligible women persists for a further 3 years. The estimated policy impact on married women's employment 1 to 3 years after potential leave take-up occurs is of 2.7 percentage points. These estimates are obtained by comparing the New Jersey sample's coefficients to those for the sample of women living in Public Use Microdata Areas (PUMAs) just outside the New Jersey border in the New York and Philadelphia metropolitan areas. As would be expected given the lower labor supply elasticities of single women and men, little evidence of policy effects are found for their employment probabilities.

The persistent positive effect on employment probability that is found in this analysis is novel in the literature. Other authors have analyzed the effect on women's employment of a similar paid family leave policy enacted in California in 2004 (e.g. Baum and Ruhm, 2013; Rossin-Slater *et al,* 2013; Das and Polachek, 2014; and Espinola-Arredondo and Mondal, 2010) but failed to find such a persistent effect on employment. The spatial differencing strategy in this paper more effectively captures differences in local economic conditions that may bias estimated policy impacts, thus revealing this persistent effect. This finding is particularly interesting since it shows how a modest financial incentive for mothers to maintain their attachment to the labor force during the year after childbirth can have a significant impact on subsequent employment outcomes.

As the comparison sample's geographic distance to New Jersey increases so do the policy's estimated impacts on employment. This is to be expected for two reasons. As distance to New Jersey increases, local economic conditions are likely to become increasingly different and by enough to affect the employment rates of potentially eligible women unrelated to the policy. Secondly, women living closer to New Jersey may be able to seek employment in New Jersey to take advantage of the policy. Therefore a clear trade-off in identification exists between being closer, diminishing bias from differences in local economic conditions, versus being further away thus reducing bias due to women in the comparison sample actually taking up the policy.

The New Jersey paid family leave policy, officially called "Family Leave Insurance", follows a similar policy enacted in California in 2004, making these the first states to explicitly have a paid leave policy in place for both male and female workers[1]. Previously, workers with no paid leave schemes through employers only had access to federal unpaid job-protected leave through the 1993 Family and Medical Leave Act (FMLA).[2] New Jersey's policy provides workers with up to 6 weeks of paid leave in order to bond with a newborn or adopted child in the year following the child's birth or adoption, but has no job protection provision.[3]

During the paid leave weeks workers earn a benefit level equal to 67% of their average weekly pay up to a cap of $584; this is calculated based on the wage earnings in the 8 base weeks preceding take-up.[4] To be eligible workers must either have earned $7,300 in the past year or worked a minimum of 20 weeks, earning at least $145 a week, in covered New Jersey employment during that time period. The program is financed through employee payroll deductions equal to 0.1% of the first $31,500 of covered wages in 2014. Although the policy could be used to take care of a sick family member, approximately 80% of policy claims are for bonding with a newborn or adopted child.[5] As with disability insurance, firms may self-insure this paid family leave program so long as their private paid leave plan is at least as generous as the state plan in both leave duration and benefit level.

Given these policy specifications, a theoretical model is developed which helps identify which individuals are more likely to be impacted by the policy. The model predicts married women whose spouses earn higher wages are more likely to be impacted and this is borne out in

[1] Rhode Island has since enacted a similar policy, effective in January 2014. While Washington signed a similar policy in 2007 but is yet to enact it, due to budget considerations.
[2] FMLA provides up to 12 weeks of job-protected unpaid leave for workers in firms that employ at least 50 workers living within a 75 mile radius.
[3] With employer approval, the 6 week total leave-taking period may be taken intermittently, in 7 day increments.
[4] The California paid family leave program has a lower replacement rate (55%) and higher maximum cap ($959).
[5] For more information on policy visit: http://lwd.state.nj.us/labor/fli/fliindex.html

the empirical results. The model further predicts that low-wage earners may not be able to afford program take-up due to one-third pay cut it entails. Results show policy impacts on employment are largest for married women with a bachelor's degree or higher suggesting these are women whose future employment outcomes are most penalized when exiting the labor force for childbearing.

As previously indicated, the finding of improved employment outcomes for women as a result of the policy is in line with some previous literature addressing employment impacts of California's paid leave policy, detailed below.[6] Baum and Ruhm (2013) use NLSY-1997 wave data and find California policy had an impact on both male and female workers' leave taking behavior. However they only find positive policy effects on mothers' employment probability nine-to-twelve months after a child's birth as well as a positive effect on hours and weeks worked that lasted into the child's second year of life. Rossin-Slater *et al* (2013) have similar findings of increases in weekly work hours of 10% to 17% and average maternity leave duration increasing from 3 to 6 weeks, using CPS data. Moreover they find evidence of wage increases associated with the policy but stress these results are not as strong. This suggests some of the perceived policy benefits may be capitalized into lower wages.

A contrasting result is found by Das and Polachek (2014) who analyze what they refer to as "unintended consequences" of California's paid leave program. They compare labor market outcomes for young versus old and men versus women in California and other states pre- and post-policy enaction. These authors confirm previous research's finding of increased labor force participation for young women, yet also find the policy increased the unemployment rate and duration of unemployment for this group of workers. They attribute these findings to policy

[6] Related work by Patnaik (2015) finds a Quebec reform to parental leave that increases fathers' leave-taking (inducing greater equity in leave-taking across parents) has persistent positive effects on mothers' labor market outcomes. This further highlights the role of parental leave provision on women's labor market outcomes.

induced changes in labor demand that favor men and older workers over younger women. Such demand changes may also contribute to the Espinola-Arredondo and Mondal (2010) results that showed no significant changes in female employment in California resulting from this policy.

Work analyzing New Jersey's paid leave policy has focused on its impact on leave-taking behavior, not on employment outcomes per se. Byker (2013) assesses how New Jersey and California's maternity leave legislation changes affect women's breaks in employment, by using Survey of Income and Program Participation (SIPP) data that allow her to track a woman's time off from work on a month-to-month basis for the 2 years before and after childbirth. She finds that these policies only have an impact on reducing the number of labor market exits lasting six months or less for women with less than a college degree. Byker (2013) suggests that this change in the pattern of labor market interruptions for less educated women may improve their employment outcomes, approximating them to those of more educated women. Sarna (2013) uses CPS data and finds evidence of an increase in leave-taking activity post-policy enaction for young women with a child under 1 years old when compared to older women, women whose young child is older, and women in other states.

Finding impacts on employment outcomes for paid family leave policies contrasts with earlier work analyzing the impact of the 1993 FMLA on leave-taking and employment outcomes including: Baum, 2003; Berger and Waldfogel, 2004; and Waldfogel, 1999. These studies conclude that the FMLA had little impact on employment and wages, claiming this is due to a combination of the FMLA being unpaid, having a short duration, and affecting a large number of employees who already had some form of privately provided maternity leave policy in place.

Paid family leave policies fall into the category of what Blau and Kahn (2013) recently called "family friendly" policies, i.e. policies that increase mothers' attachment to the labor force during childbearing years. These authors report that up to 28% of the U.S.'s relative decline in female labor force participation in comparison to other developed countries since 1990 may be attributable to such policies. Similar results are found by Cipollone, Patacchini, and Vallanti (2014) in assessing differences in female employment outcomes across 15 European Union countries. Their work indicates family oriented policy changes may explain up to 25% of young women's increased labor force participation in these countries in the last 20 years.

The findings in this paper also contribute to the literature that seeks to explain regional differences in women's labor force participation due to other factors affecting childrearing arrangements (e.g. Black *et al,* 2014; Compton and Pollack, 2013; and Graves, 2013). A related strand of research has analyzed the impact of paid leave legislation on outcomes for children of leave-taking parents (e.g. Baker and Milligan, 2008; Carneiro *et al,* 2010; Rasmussen, 2010; Rossin, 2011; and Ruhm, 2000) and fertility decisions (Lalive and Zweimuller, 2009; Malkova, 2014). While this paper does no such analysis, it is important to keep these impacts in mind when considering the policy's welfare implications.

The remainder of the paper proceeds as follows: Section II presents the household labor supply model that provides the theoretical framework for the analysis; Section III describes the data used in the analysis; Section IV details the identification and econometric methods used; Section V discusses the empirical results; and Section VI provides a conclusion.

2.2 Theoretical Model of Two-Period Household Labor Supply

In order to assess how individuals will react to the enaction of paid family leave legislation this paper makes use of a two-period household labor supply model where individuals maximize utility over: leisure (L); a consumption good (X); and the choice of having a child (C).

In the first period, the leave take-up period, the individual decides whether or not to have a child as well as whether to take-up paid family leave. In the second period, which represents the rest of their lives, utility function and earnings will therefore reflect whether they: had a child; decided to take-up the policy; and decided to return to work. Therefore person *i* will maximize the following two-period utility function, where *r* is the discount rate and *t* denotes the time period:

$$U_i\left(X_{i,t}, L_{i,t}, C_i\right) = U_{i,1}\left(X_{i,1}, L_{i,1}, C_i\right) + \frac{U_i\left(X_{i,2}, L_{i,2}, C_i\right)}{1+r} \qquad (1)$$

Utility maximization is subject to time, income, and child sustenance budget constraints that are a function of the decisions to have a child and take-up the policy. If the individual chooses not to take-up paid family leave the two-period full-income budget constraints take the following usual form, where $w_{i,t}$ is the wage rate for individual *i* in time period *t* ; *T* is the total time units available in each period; and $y_{i,t}$ is individuals *i*'s non-labor income, which includes spousal income transfers[7]: $Tw_{i,1} + y_{i,1} \geq w_{i,1}L_{i,1} + X_{i,1}$; and $Tw_{i,2} + y_{i,2} \geq w_{i,2}L_{i,2} + X_{i,2}$.

By contrast, if said person chooses to take-up paid family leave then the two-period full-income budget constraints become: $T \geq L_{i,1}$; $y_{i,1} + (2/3)\overline{hw} \geq X_{i,1}$; and $Tw_{i,2} + y_{i,2} \geq w_{i,2}L_{i,2} + X_{i,2}$. This reflects the fact that in the first period the individual now earns two-thirds of their average wage income ($\overline{hw}$) and works zero hours[8]. Whenever someone chooses to have a child the following child sustenance budget constraint must also be satisfied: $X_{i,t} \geq X_{minC}$.

Figure 2.1 shows the first period budget constraints that the individual faces when making their choices. The first thing to notice in Figure 2.1 is that paid leave policy take-up

[7] Following the method of Black *et al* (2014) and Chiappori (1992) this paper assumes the household will a *priori* decide on a sharing rule such that each individual will receive income from their spouse in each period. Although Black et al (2014) use this method in a setting where the household is actually only making their choices in one period, for simplicity I assume such a sharing rule choice can be repeated at the beginning of each period in the two-period model.

[8] Recall that the paid leave benefit amount is calculated based on the average earnings in the 8 base weeks preceding leave take-up. A base week is a week in which someone earns at least 20 times New Jersey's minimum hourly wage. This means that both the wage rate and the hours worked in those 8 weeks impact the paid leave benefit level.

introduces a kink into the budget constraint, leading people to consume the bundle $(y + (^2/_3)\overline{hw}, T)$ if they take-up the policy. Secondly, the existence of the child sustenance constraint implies that anyone whose average wage income is such that $\overline{hw} < {^3/_2}\,(X_{minC} - y_{i,1})$ cannot afford to take-up the program since they will not have a consumption level above the minimum required for child sustenance (X_{minC}). This means that, all else equal, lower-wage workers are less likely to take-up the program. It is however important to highlight public assistance programs may add to the non-labor income of lower wage workers and help them meet the child sustenance constraint, thus allowing them to take-up the program. Such programs include Temporary Assistance for Needy Families (TANF) and Supplemental Nutrition Assistance Program (SNAP). Similarly, the higher the level of spousal income transfers (captured in $y_{i,1}$) the more likely someone can afford to take-up paid family leave.

As noted earlier, a complementarity exists between the two periods that can arise through the direct effect on second period utility of having a child (C_i), wage ($w_{i,2}$) and non-labor income ($y_{i,2}$) changes in the second period, and changes in preferences. All these factors are potentially impacted by the decision to take-up paid leave and hours worked in the first period.

Wage in the second period is assumed to be an increasing and concave function of hours worked in the first period. Therefore people who leave the labor force for childbearing, without any leave take-up, will suffer a wage penalty when returning to work. This wage penalty is probably higher the more specialized the human capital required to carry out the job, particularly so in employment with fast-changing production processes. Second-period non-labor income is similarly impacted when mothers decide to leave employment for childbearing because of the search costs associated with finding a new job when returning to work. New mothers may face particularly high job search costs when returning to employment since there could be discrimination from employers reluctant to hire someone who has a young child to take care of. If instead the worker maintains their tie to the first-period employer through leave take-up, no job search costs are accrued in the second period.

Second-period wage and non-labor income impacts of paid leave take-up described in the preceding paragraph represent income and substitution effects of the policy. These can contribute towards the policy having a long-lasting positive effect on employment for women who would otherwise be likely to leave employment for childbearing. Note that if these workers were otherwise able to make use of the Family Medical Leave Act of 1993, it is unlikely such income effects would be significantly different once the paid leave policy is in place. This is because FMLA guarantees 12 weeks of job-protected unpaid leave, meaning workers can return to their previous employment after such unpaid leave periods. However, due to different eligibility requirements fewer workers can use FMLA than the New Jersey paid leave policy.

Preference changes associated with policy take-up may also arise in multiple forms. Mothers who drop out of the labor force for childbearing may change their preferences in such a way that it decreases their likelihood of working in the future; e.g. getting used to being near their child and thus being reluctant to return to work. Analogously, mothers who do take-up paid leave may get a better gauge on how to balance work and childrearing requirements; thus making them more likely to remain employed in the first years of their child's life.

An alternate mechanism through which preferences may be impacted is via an emotional tie generated between the employer and employee. This could arise if the paid leave taker feels an obligation to return to work due to the fact that they were being paid during the time they took off, and therefore may feel guilty if they leave employment after making use of the policy. Expectations regarding leave-taking behavior may also be changed due to the availability of this public paid leave policy. Whereas previously workers with access to private leave schemes through their employers may have felt negatively stigmatized by their employers for taking paid leave; the widespread availability of paid leave may reduce that stigma since the majority of workers in the state now have the ability to use it. This would results in greater use of paid leave schemes in general. Although these mechanisms cannot be identified using this paper's estimation strategy, they may be strong drivers of the long-lasting effect on women's employment that the paid leave policy is found to have.

Overall, the differential implications of the model based on own wage rate and levels of non-labor income point towards analyzing heterogeneous impacts based on marital status as well as both own and spouse education levels. Own education will be positively correlated with own wage level. While spouse's education, through its correlation with spouse's wage level, will be correlated with spousal income transfers thus affecting non-labor income. The paid leave policy enaction is likely to have the highest impact on the probability of employment of someone who absent the policy has a low likelihood of being employed when having a child.

2.3 Data and Summary Statistics

Data for the analysis is obtained from the American Community Survey (ACS) from 2005 to 2012, via the IPUMS-USA website (Ruggles *et al*, 2010). This dataset contains information on a series of socio-demographic characteristics of surveyed individuals as well as detailing where they live and work. The advantage of using ACS data is that the sample is large enough to enable spatial differencing across fairly small geographic areas, detailed below.

The analysis is carried out for six different samples at varying distance ranges from the New Jersey border. The samples contain individuals residing in four broad geographic areas, these being: New Jersey; the New York and Philadelphia metropolitan areas; neighbor states, outside the previously detailed metropolitan areas; and in all other states.[9]

The neighbor states sample includes people residing in the states of Delaware, New York, and Pennsylvania and is broken down into two estimating samples depending on how close to the New Jersey border the particular Public Use Microdata Areas (PUMAs) are. People living in PUMAs within 60 miles of the New Jersey border are in one estimation sample; those in PUMAs further away from this border are in another.[10] For the New York and Philadelphia metropolitan areas the estimation sample is similarly broken down based on distance to the New Jersey border. One sample contains people living in PUMAs within these metropolitan areas that share a border with New Jersey but are outside the state of New Jersey[11]. While the other sample only contains people living in PUMAs further away from the New Jersey border. This breaking up of areas by distance to the New Jersey border is done in order to reflect different likelihoods of being able to take advantage of the policy by seeking employment in New Jersey.

In all estimating samples the analysis is restricted to individuals aged between 18 and 40 years old in order to focus on workers of childbearing age. The socio-demographic variables included in the analysis are: educational attainment; ethnic group; marital status; and age. Table 2.1 displays summary statistics for these variables for women living in the four broad geographic areas in the analysis. Statistics are reported separately for all women and for those that are potentially eligible for the paid family leave policy. A person is deemed potentially eligible if they had a child born after the legislation enaction, concretely in 2009 or later[12]. It is important

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[9] All other states excludes New Jersey and its bordering states (DE, NY, and PA), while California is excluded due to it having a paid family leave policy of its own.
[10] All PUMAs in Delaware are within 60 miles of the New Jersey border, hence are not included in this last sample.
[11] These PUMAs are typically within 10 miles of the New Jersey border.
[12] No restriction is placed on where the individual may have been living when they gave birth. As a robustness check regressions are also run on a restricted sample which only includes individuals who moved into their home 5 or

to emphasize the analysis can only identify intent-to-treat effects, since we cannot observe whether or not someone actually took-up the paid family leave policy.

By assessing the difference in these variables across geographic areas one can conclude that women living in New Jersey and in New York and Philadelphia have on average higher education and are more ethnically diverse, than those in the other two areas. Looking at the differences between panels A and B further reveals that potentially treated women have, on average: lower employment rates; higher education levels; are more likely to be married; and are slightly older than the women in the sample as a whole.

As previously mentioned, results will be compared across geographic areas. One concern for identification would arise if the differences between potentially treated and untreated women was markedly dissimilar across geographic areas; thus making such cross-geographic areas comparisons inadvisable. Table 2.1 allows us to see this is not the case, indicating these comparisons will be useful for identification.

Evidence in support of the geographic differencing strategy employed is provided by the evolution of employment rates across these areas in the years of analysis. Figure 2.2 shows the trends in the employment rate for women who are potentially eligible, those with a youngest child 3 years old or younger, and ineligible, those with no child or a youngest child older than 3, for three of the estimation samples. One can observe the employment rate of potentially treated women trended upward in the years before 2009 while for the control group the upward trend is slightly less pronounced. This may constitute a violation of the parallel trends assumption required for a typical difference-in-differences setup. However Figure 2.2 also reveals that the trends for treatment and control groups display similar patterns across geographic areas.

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more years ago; thus indicating they probably gave birth in the same state they currently reside in. Results do not change significantly although there is smaller power due to the reduced number of observations (see Table A1-1).

Concretely, across these areas the employment rate of potentially treated women grew at a faster rate in the years leading up to the policy than that of the control group.

Furthermore, Figure 2.2 shows that the trend in women's employment in the sample that is closest to New Jersey (PUMAs inside New York and Philadelphia metropolitan areas that border New Jersey) is most similar to that for New Jersey. This highlights the importance of comparing results across geographic areas in order to accurately account for local economic conditions that may bias a typical difference-in-differences estimate of the policy's impact on employment. It also indicates that the areas closest to New Jersey are likely to be the preferred comparison groups due to conditions being most similar within close geographic proximity.

Figure 2.2 provides no indication of the policy increasing employment for potentially eligible women in New Jersey. However, this unconditional distribution of employment masks the effects of the policy on employment which are evident in the empirical analysis that follows.

2.4 Identification and econometric method

In order to identify the effects of the paid family leave policy on the employment outcome of workers, this paper employs a spatial differencing strategy consisting of two steps. Initially a series of difference-in-differences estimates of the policy's impact on employment are computed for all six estimating samples. These difference-in-differences estimates are calculated using the regression specifications described in estimating equations (2) and (3). The difference in these estimates relative to the estimate obtained from the New Jersey sample is then calculated and a one-sided test of whether the New Jersey estimated coefficient is larger than those for other samples is carried out; thus indicating significant policy effects on employment.

The analysis is carried out using a linear probability model where the outcome is whether or not a person was employed in the week preceding the survey. The estimating equation is:

$$employed_{i,s,t} = \alpha + \partial_1\, Currently\ Eligible_{i,t} + \partial_2 Eligible\ 1\ to\ 3\ Yrs\ Ago_{i,t}$$
$$+\partial_3\, Post2009 + \beta X_{i,t} + \lambda_{s,t} + \gamma_{i,t} + \varepsilon_{i,t} \qquad (2)$$

The first two variables in equation (2) capture the impact of the paid family leave legislation on employment for person i, in state s and year t. $Currently\ Eligible_{i,t}$ indicates whether a person is currently potentially affected by the paid family leave policy. It is computed as the interaction of an indicator for having a child the under age of 1 and an indicator for the year being 2009 or later. While $Eligible\ 1\ to\ 3\ Yrs\ Ago_{i,t}$ indicates whether a person could potentially have been affected by the paid family leave policy in a previous year, based on the age of their youngest child.[13] While the first variable aims to capture the policy's immediate impact on employment, the second attempts to capture any longer-lasting effects. Therefore ∂_1 and ∂_2 are the primary coefficients of interest in assessing policy impacts on employment.

The vector of own attributes ($X_{i,t}$) in equation (2) includes all the variables presented in Table 2.1 in addition to the education level of spouses for married individuals. Therefore the variable indicating whether someone is married also indicates being married to a spouse that has less than a high-school degree. The inclusion of these variables is critical since spouse's education level is highly correlated with their wages and therefore will serve as a proxy for the amount of intra-household income transfers that occur, thus affecting employment probability. As highlighted in the model in Section II, the larger the amount of income received from a spouse the more likely one would be able to drop out of the labor force for childbearing since the spouse would be able to cover the consumption costs associated with having a child. Therefore indicating the paid leave policy may bring these people back into employment, since they can take advantage of the extra income during the paid leave period.

[13] For example, a women with a 2 year old child in 2011 is classified as being potentially treated since that child would have been born in 2009.

The remaining variables in the regression are youngest own child age indicators ($\gamma_{i,t}$) and state by year fixed effects ($\lambda_{s,t}$). The former are included since the age of a woman's youngest child significantly impacts their employment probability and, since the policy variables are a function of youngest child age, their omission would likely bias the results[14]. The latter are included to capture variation in employment rates across states and time, the omission of which would likely bias results. Ideally individual fixed effects would also be used however the ACS data is a repeated cross-section, so these are unavailable.

In order to identify how persistent the effects on employment are, a model is run which captures differential impacts by youngest child age. Equivalently, this also assesses differential impacts based on how many years have elapsed since potential leave take-up. This specification is shown below:

$$\begin{aligned} employed_{i,s,t} = {} & \alpha + \partial_1\, Post\ 2009 * Child\ Under\ Age\ 1_{i,t} \\ & + \partial_2 Post\ 2010 * Child\ Age\ 1\ to\ 2_{i,t} + \partial_3 Post\ 2011 * Child\ Age\ 2\ to\ 3_{i,t} \\ & + \partial_4 Post\ 2012 * Child\ Age\ 3\ to\ 4_{i,t} + \sum_{n=2009}^{2012} \partial_n\, Post_n \\ & + \beta X_{i,t} + \lambda_{s,t} + \gamma_{i,t} + \varepsilon_{i,t} \qquad (3) \end{aligned}$$

The medium-term impact of the policy is split into three different variables based on whether a person was potentially impacted one, two, or three years ago. The analysis stops at three years since the last year of data is 2012.

Throughout the analysis, standard errors are clustered at the PUMA level in order to account for potential serial correlation in outcomes within a geographic area that may bias the

[14] Youngest own child age indicators are split in the following manner: under age 1; age 1; age 2; age 3; age 4 to 10; age 11 to 14; and age 15 to 18.

precision of estimated policy impacts.[15] Regressions are run separately for men and women and for women the analysis is further split by marital status. This is done in order to reflect the differing likelihoods of being impacted by the policy. In the same spirit, subsequent analysis interacts the policy eligibility variables with own and spouse education level. This captures the heterogeneity in impact for these groups suggested by the theoretical model.

Previous research analyzing labor market effects of paid leave policies has tended to compare the outcomes of younger women to older women, reflecting their differing likelihoods of making use of the policy (e.g. Das and Polacheck, 2014). While this sort of comparison is informative, it cannot identify whether the employment impacts are all occurring at the time the paid leave policy is used or whether they arise in the years following policy usage. However, the advantage of such a method is that it does not rely on using the age of an individual's youngest child as an indicator of whether or not they were policy eligible. The analysis in this paper does determine potential eligibility based on youngest child age, and so can assess how persistent employment effects may be. Identification therefore relies on the assumption that the decision of when to have a child is exogenous to the policy enaction. The validity of this assumption is assessed in a robustness check where predicted youngest child age instead of actual youngest child age is used to indicate potential policy eligibility.[16]

The analysis concludes with a final robustness check analyzing whether some other New Jersey specific factor affecting maternal employment rates post-2009 may be driving the results. This is done by comparing the post-2009 employment outcomes of women whose youngest child was born in 2008, thus policy ineligible by one year, versus having that child be born in 2009.

[15] The specifications in equations (1) and (2) are also run for all samples in a single estimation; thus allowing for the state level clustering of standard errors. Results are available upon request and confirm the findings detailed later on.
[16] An analysis similar to that of Das and Polacheck (2014) is also carried out. It shows that positive effects on employment are evident for young married women (18 to 40), particularly those married to spouses with a BA degree or higher, when compared to similar women of older age (41 to 60). See Table A1-2 for the results.

2.5 Results

2.5.1 Baseline model

Table 2.2 presents the full results from estimating equation (2). The remaining tables only report the variables pertaining to the impacts of the paid family leave legislation since these are the primary variables of interest and the remaining coefficients do not change significantly across model specifications.

The most salient feature in Table 2.2's results is that both the coefficients associated with the paid family leave policy are positive and generally significant across different samples. This highlights the importance of analyzing the difference in the coefficients across geographic samples since the economic conditions at the time, namely the "Great Recession", are likely to have important impacts on employment across the samples. Concretely, those that would have typically been out of the labor force, namely mothers of newborns, could be drawn into work due to the economic hardship households faced.

One can observe that for the coefficient indicating current potential policy eligibility (*Currently Eligible*) the magnitude of the difference between the New Jersey sample coefficient and those from other samples tends to increase as that sample's distance to New Jersey increases. This is to be expected for two reasons. The first is that the further away from New Jersey the sample is, the more likely it is that other factors may be differentially affecting the employment rates of potentially eligible women, thus potentially contributing to greater differences in the coefficients that may not reflect true policy impacts. Secondly, women living closer to New Jersey may be able to seek employment in New Jersey to take advantage of the policy. This makes estimated policy coefficients for areas closer to the New Jersey border become closer to the ones for the New Jersey sample.

The estimated policy impacts on employment in the year one is currently eligible for the policy range from a 0.6 to 2.8 percentage points increase, depending on the control sample used. These are seen in the square brackets underneath the estimated coefficients. These effects are generally not statistically significant though, reflecting the fact that single women may not be heavily impacted by the policy. This will come through in the analysis which splits the women sample by marital status, shown in Table 2.4.

The variable indicating a person was potentially eligible for paid family leave between 1 and 3 years ago shows significant estimated policy impacts across all comparison samples. The estimated impacts range from a 1.9 to 4.4 percentage point increase in employment probabilities, or 2.8% and 6.6% respectively relative to the mean employment rate for women in New Jersey during this period. This is indicative of the policy having long lasting effects on women's employment, which will be further investigated in subsequent analysis.

Table 2.2 shows the remaining control variables' coefficients have the signs labor theory would predict and are similar across samples. Unsurprisingly, higher educational attainment increases employment probability and own age has a positive and concave relationship with employment. The racial breakdown shows minorities generally have lower employment rates than the excluded white race category. Marital status is shown to adversely affect women's likelihood of being employed while having a spouse with a BA degree or higher educational attainment tends to further decrease that likelihood. Interestingly, having a spouse with a high school degree or some college makes a woman more likely to work than if her spouse has less than a high-school degree. It is possible that being married to an individual with less than a high-school degree indicates both you and your spouse have a low attachment to the labor force, thus leading to this negative effect on employment relative to higher spouse education levels.

Youngest child age is shown to play an important role in determining employment probability. Having a youngest child under the age of 10 is consistently associated with lower employment, while having a youngest child between the ages of 11 and 18 means you are more likely to be employed than women with either no children or a youngest child that is older. These results highlight the importance of controlling for youngest child age in estimating equations.

By comparing results for women to those for men, shown in the Table 2.3, one obtains further evidence supporting the view that the impacts for women are credibly due to the paid family leave policy enaction. For men there are no significant differences between the New Jersey sample's estimated policy coefficients and those for all but one of the geographic areas in the analysis. The exception occurs when comparing the outcomes for men in New Jersey to those living in the Philadelphia and New York metropolitan areas in non-border PUMAs. For this comparison the results suggest a positive policy impact on men's employment. However, since all the other estimates show no such significant impacts, this may indicate some other factor unrelated to the policy at hand is likely driving this result. This therefore impacts the credibility of policy estimates obtained when comparing the New Jersey coefficients to those from the sample in column (3).

Finding no credible paid leave policy impacts on male employment is in line with what one would expect given the stronger labor force attachment and lower extensive margin (i.e. work or not) labor supply elasticity men typically exhibit. These results support the conclusion that it is not some other New Jersey specific shock to employment that is driving the state's increase in employment for mothers with a child born after 2009.

As predicted by the household labor supply model, Table 2.4 shows that married women are the ones significantly affected by the paid leave policy, and no significant effects are seen for single women. Since single women have less flexibility in their labor supply decision, they are less affected than married women by a policy that induces women to remain in the labor force during their child's first year of life. For married women we can observe the *Currently Eligible* variable coefficient is significantly different between the New Jersey sample and all other samples except the one in column (3); whereas the *Eligible 1 to 3 years ago* variable coefficient is significantly different between the New Jersey sample and all other samples. These estimated policy impacts tend to be larger than for the all women sample shown in Table 2.2.

If one assesses the impact of the policy on New Jersey married women's employment relative to those living in border PUMAs within the NYC and PHL MSAs, we can see being currently eligible increases employment probability by 3.1 percentage points and previous eligibility increases it by 2.7 points. This shows that even when comparing across areas that are very close together one obtains evidence of a significant policy impact on employment.

The sample in column 2 is likely to have the most similar economic conditions to those in New Jersey, thus providing the preferred control group. However it is possible women in this sample may seek employment in New Jersey to take advantage of the policy, thus leading to smaller estimated policy impacts. Estimated impacts in column 3 are slightly smaller, though not significantly so. However, given that for this sample there is a significant difference in post-policy enaction employment for men relative to New Jersey, one becomes sceptic regarding the credibility of policy estimates obtained using this sample.

As the distance of the comparison sample to New Jersey increases, the likelihood of women seeking jobs in New Jersey in order to take-up the policy decreases. Accordingly, estimated policy impacts on employment when comparing New Jersey to the three remaining samples (columns 4,5, and 6) are larger than the ones obtained when using column 2 as the comparison group. However, as previously highlighted, if the comparison group becomes too distant from New Jersey the local economic conditions may differ enough that they can bias estimated policy impacts. Given this, of the estimates presented in columns 4 to 6, the one for column 4 is preferred since it is closest to New Jersey. For this comparison sample the estimated policy impacts are of 3.8 and 5.0 percentage point increases in employment in the year of eligibility and in the three years after potential take-up, respectively. These estimated effects are slightly larger than the ones obtained when comparing New Jersey outcomes to those for individuals in column 2's sample, though not in a statistically significant manner. For the remaining columns both the *currently eligible* and *eligible 1-3 years ago*, estimated policy impacts on employment are also positively significant.

Overall, the findings for married women suggest there is a significant policy impact on employment in the year one is currently eligible for policy take-up of between 3.1 and 4.1 percentage points. A similar magnitude effect is found 1 to 3 years after potential policy take-up, although the range of estimates is wider, showing an estimated impact between 2.7 and 5.0 percentage points.

2.5.2 Duration of paid family leave policy's impact on employment

Having found persistent effects on married women's employment probability associated with the policy, the results in Table 2.5 show the breakdown of the policy's impact by years since possible take-up may have occurred. These are obtained using the model in estimating equation (3). If one looks at column 2, the sample for women living in PUMAs that border New Jersey, inside the NYC and PHL MSAs, one observes that the policy has a significant policy impact on employment in the year of potential eligibility and 3 years after being potentially eligible. Across the years since potential take-up the estimates are not different in a statistically significant manner, but they do range from 1.8 to 7.1 percentage points. These results are suggestive of real policy impacts on employment up to three years after policy take-up.

When analyzing the results for the next best comparison group, the one containing married women living in DE, NY, and PA PUMAs that are within 60 miles of the border but outside the NYC and PHL MSAs, shown in column 4, the policy has significant positive impacts on employment in the year of potential take-up and 1 year after. The estimated magnitudes of the policy impacts across years since potential take-up have a smaller range than those in column 2, ranging from 3.8 to 5.4 percentage points. Estimated impacts are similar in columns 5 and 6 and are again significant in the year of potential take-up and one year after.

The estimated impacts for individual years after potential take-up are not all statistically significant but the magnitudes of the effects suggest this is due to larger standard errors not smaller coefficient estimates. In contrast, when lumping all the years after take-up into a single variable (*eligible 1-3 years* ago) the estimated policy impact is statistically significant. Overall, the analysis shows these policy impacts on employment may persist for up to three years after potential leave take-up. This is a novel finding and points towards the importance of temporary financial incentives for mothers to remain in the labor force during their child's first year of life having significant impacts on subsequent employment outcomes.

2.5.3 Heterogeneous policy impacts by own and spouse educational attainment

The household labor supply model presented in section II indicated there are likely to be differential policy impacts based on own and spouse educational attainment. Tables 2.6 and 2.7 present results from model specifications that seek to identify this heterogeneity in impacts.

Table 2.6 shows the immediate employment impact of the policy is stronger among married women with some college experience or higher educational attainment. When comparing the outcomes for women in New Jersey to those in column 2, the estimated impact on mother's employment in the year they are eligible for paid leave is of 6.5 and 5.9 percentage points for those with some college or a BA degree, respectively. The estimate for subsequent employment is again strongest for women with a BA degree or higher educational attainment, showing a 5.2 percentage point increase in employment probability in the three years after leave-taking. Results from other comparison samples generally follow this pattern.

These findings are consistent with the theoretical model that showed lower-wage workers (typically lower education levels) were less likely to take-up the policy due to not being able to afford the one-third pay cut in those 6 weeks of paid leave. They are also in line with those of Cipollone *et al* (2014) that showed family oriented policy changes, such as maternity leave, had a higher impact on the labor force participation of women with medium-to-high education levels. Furthermore, they may indicate that less educated workers have lower stores of wealth, making it again less likely that they could afford to drop out of the labor force when having a child.

Previous authors found these paid leave policies tend to have a larger impact on leave-taking of lower educated and minority workers (Byker, 2013; Rossin-Slater *et al*, 2013). In contrast, results here indicate long-lasting employment impacts are evident for women with higher education levels. This suggests these are women whose subsequent employment outcomes are most penalized for dropping out of the labor force for childbearing, which may reflect higher job search costs and wage penalties associated with returning to work. Although more educated women are generally more likely to have a paid leave scheme through their employers and therefore less likely to be impacted by the policy enaction; the legislation may have forced employers to improve their leave schemes in order to meet the standards of the state plan. This may drive more mothers to take advantage of employer provided paid maternity leave schemes after the policy enaction. Thus driving the effects found for higher-education women.

For the policy impact breakdown by spouse education level, shown in Table 2.7, results are in line with the household labor supply model's prediction. They generally show that higher spouse education levels are matched with larger policy impacts. This likely comes about because spouses with higher education will typically have higher wages and therefore impact subsequent income transfers between spouses. That being said, there is evidence of a significant policy impact in the year a women is potentially eligible for paid family leave for women married to spouses who have less than a high-school degree. This effect however is not present in the years after potential leave policy take-up. This may indicate women in this group are likely to take advantage of the policy but after benefits expire they revert back to their lower level of attachment to the labor force, while more educated women remain employed.[17]

2.5.4 Robustness checks

One concern with the results found thus far is that the increase in employment found for married women in New Jersey post-paid family leave policy enaction could be due to some other factor that differentially affected the labor supply of mothers in New Jersey versus other areas. As a robustness check, Table 2.8 presents results from an analysis which compares the outcomes post-2009 for women with a child born in 2009, hence eligible, to those with a child born in 2008, hence ineligible by one year.

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[17] As a robustness check, the model used in Table 7 was also ran on a sample consisting only of women with some college experience. This was done so as to guarantee the differential impact by spousal education level was not simply a reflection of assortative mating based on education level, thus leading to erroneous conclusions regarding spousal education level's influence on outcomes. The findings confirm that higher spousal education levels increase employment impacts of the policy even among women with similar education levels. (available upon request)

Results show no significant impact on the employment of married women with a child born in 2008, but do show significant impacts for those with a child born in 2009. The estimated impact for those with a child born in 2009 is of 4.6 percentage point increase in employment probability when compared to women in column 2's sample, the preferred comparison group. The estimated impacts for women with a child born in 2009 are significant when comparing New Jersey results to those in columns 2, 4, 5, and 6; as was the case in the previous analysis. Finding no significant policy effects for married women with a child born in 2008 shows the results obtained thus far are not due to some other factor affecting the employment rate of mothers in New Jersey post-2009.

The final robustness check addresses the possibility individuals may endogenously choose when they have a child in response to the paid leave policy's enaction. Although this is certainly possible, given the relatively small amount of compensation that individuals get for making use of the policy (up to 6 weeks at two thirds their pay rate), the policy may not be a strong driver of this decision.

The model in Table 2.9 analyzes this endogenous child fertility decision due to the paid leave policy by obtaining the predicted probability that someone has a youngest child under the age of 4 and interacting this with a post-2009 indicator. Having a child under the age of 4 indicates being potentially eligible for the policy at some point during the sample periods and is estimated by the average probability of having a child under the age of 4 in the year 2000 Census for individuals with specific combinations of: age; gender; marital status; education; and white race status. Given endogeneity concerns, no youngest child age indicators are used in this model.

Panel A in Table 2.9 shows the results from a model that uses the actual youngest child status and the results are similar to the original model shown in Table 2.2. Panel B uses the predicted youngest child status and one can observe that the predicted youngest child status has a similar impact to the actual status in Panel A, namely a significant negative impact on employment probability. This is encouraging since it indicates the predicted child status is a good proxy for actual child status. In comparing estimated policy impacts in Panel A versus Panel B for column 2, our preferred comparison group, one observes the estimated impact is larger using predicted child status than when using actual status. In neither of these is the estimated impact significant. In a sample where estimated impacts are significant, such as in column 6, the estimated impact in Panel B is 4 percentage points larger than the one in Panel A.

Estimates from the model in Panel B are typically larger than those in Panel A, suggesting there may be a downward bias in the estimated impacts from the model. This would occur if the women who endogenously choose to have a child due to the policy's enaction are generally less likely to be in the labor force, thus driving down the estimated impacts on employment.[18] This makes sense if these are women who are marginally attached to the labor force but decide to take advantage of the policy in order to obtain the financial compensation it entails. Overall the results in Panel B are similar to those in Panel A but with larger standard errors given the imperfect ability to predict women's youngest child status. This suggests estimated policy impacts are valid and not simply a result of endogenous fertility decisions.

[18] Alternatively, estimated impacts using the predicted child status could be biased upward if the instruments for actual child status and potential policy eligibility were weak. Two-stage least squares estimations show this is not the case. The first-stage F statistics for the instruments are large (F-stats all above 100), indicating the instruments are good predictors of actual child status and potential policy eligibility.

2.6 Conclusion

This paper sheds new light on how increasing mothers' attachment to the labor force immediately after child birth can have a significant effect on subsequent labor market outcomes. It does so by making use of New Jersey's 2009 paid family leave legislation enaction and employing a spatial differencing strategy that captures its impact on the employment probability of women. The preferred specification shows an estimated policy impact of a 3.1 percentage point increase in the employment probability of married women in the year they are potentially eligible for policy take-up. A similar magnitude increase of 2.7 percentage points is also evident in the three years after potential leave take-up. Such estimates respectively represent a 4.1% and 4.7% increase relative to married women's employment rate in the state.

This shows how a relatively small financial incentive for maintaining a mother's tie to the labor force during the year immediately following childbirth can have an enduring effect on their labor market outcomes. This persistent effect is novel in the literature and suggests expanding such a policy to other states may lead to improvements in employment outcomes for women in the years following childbirth.

The estimates detailed above are obtained by comparing the New Jersey sample to that of married women living in Public Use Microdata Areas just outside the New Jersey border inside the New York and Philadelphia metropolitan areas. Estimated impacts obtained by comparing New Jersey to samples at a greater distance to New Jersey are generally larger, but may reflect differing local economic conditions thus not providing as strong an evidence of policy impacts. As would be expected given their lower flexibility regarding the decision to participate in the labor force, little evidence of policy effects is found for single women and men.

Finding positive family leave policy impacts on employment is in line with some previous research addressing this issue, e.g. Byker (2013), Baum and Ruhm (2013), Rossin-Slater *et al* (2013). However the results contrast with those of Das and Polachek (2014) and Espinola-Arredondo and Mondal (2010) who find that a similar legislation in California had no effects or actually worsened employment outcomes of young women in the state. This difference may arise due to the spatial differencing method employed in my analysis.

Further work shows estimated policy impacts are larger for married women with higher education levels or married to husbands with higher education levels. While the latter is expected, given these are women who would have previously been likely to leave the labor force to have a child since their spouse would be able to aid them financially during this time. The former suggests women with higher education levels suffer greater shocks to their future employment probability when dropping out of the labor force for childbirth.

The findings here confirm the importance of "family friendly" policies in enhancing women's labor force attachment during childbearing years, similar to findings in Blau and Kahn (1997 and 2006); Kim and Polachek (1994); and Cipollone *et al* (2014). It also highlights how childbearing arrangements impact regional differences in women's employment, consistent with Graves (2013); Black *et al* (2014); and Compton and Pollack (2013).

Future research would benefit from concentrating on identifying the mechanisms which drive the persistent effect on mothers' employment that is found here. Of particular interest is whether these long-lasting employment effects are coming about through income or substitution effects of the program, i.e. impacts on wage and job search costs, or changes in preferences over work and leisure that drive mothers to stay in the workforce following childbearing.

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Figure 2.1
First period budget constraint with and without paid family leave take-up

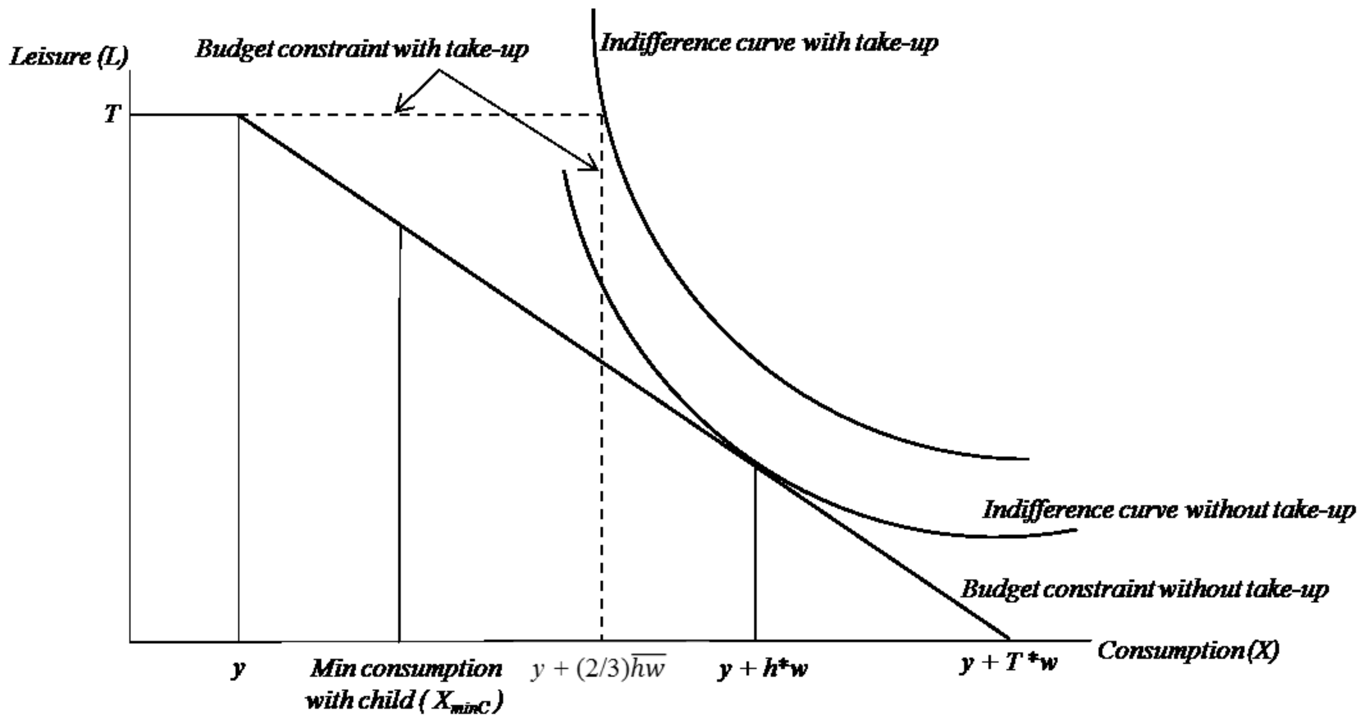

Figure 2.2
Employment rates for women aged 18 to 40 by youngest child age (2005-2012)

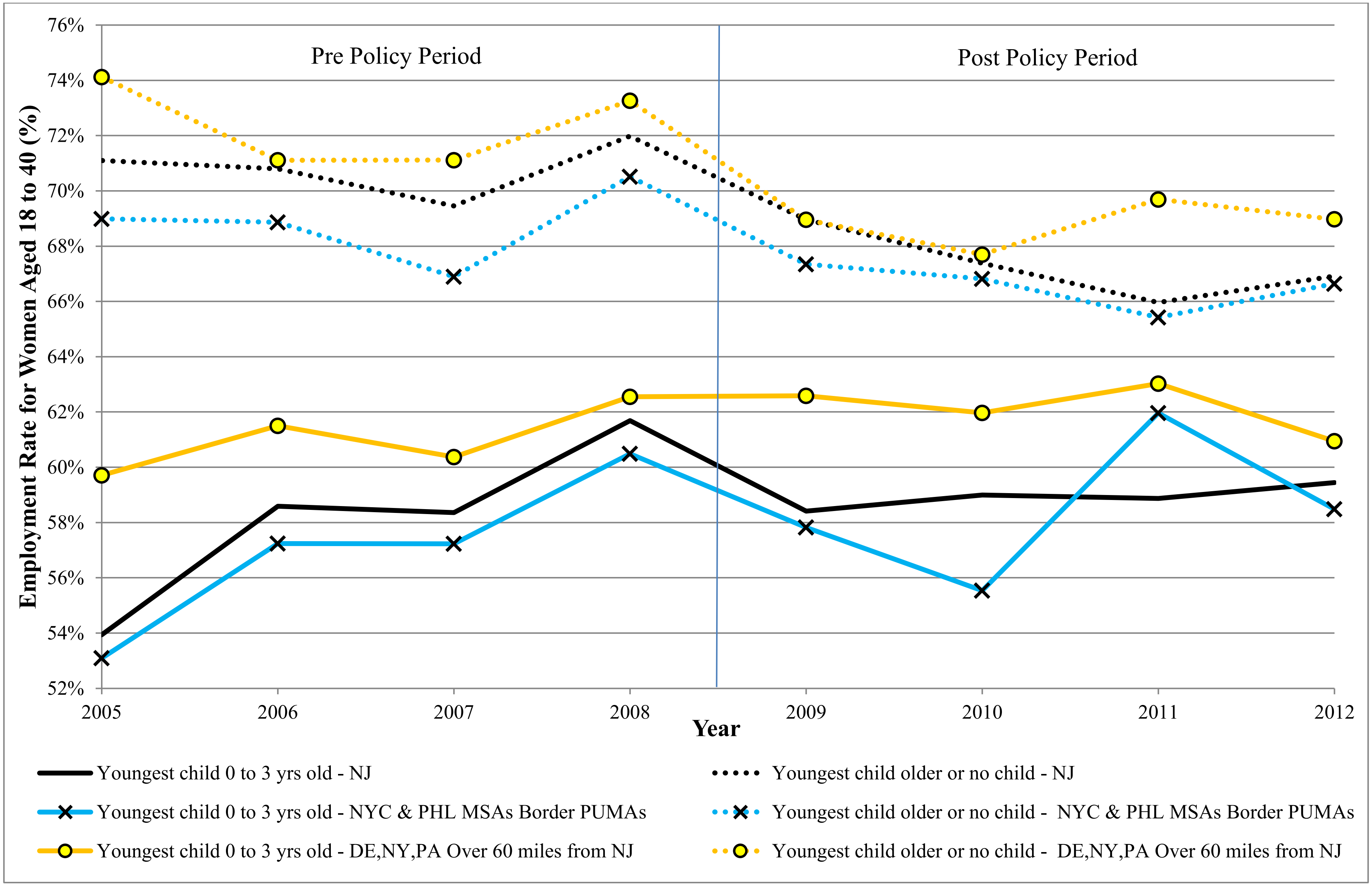

Table 2.1
Summary statistics by residential location 2005-2012

Panel A: All women Aged 18 to 40

	New Jersey		NYC and PHL MSAs[b]		DE, NY, and PA[c]		All Other States[d]	
	Mean	(S. D.)	Mean	(S. D.)	Mean	(S. D.)	Mean	(S. D.)
Personal Attributes								
High School Degree	0.241	(0.428)	0.216	(0.411)	0.269	(0.444)	0.250	(0.433)
Some College	0.312	(0.463)	0.293	(0.455)	0.375	(0.484)	0.373	(0.484)
BA Degree or More	0.355	(0.478)	0.372	(0.483)	0.265	(0.441)	0.259	(0.438)
Hispanic	0.206	(0.405)	0.222	(0.416)	0.053	(0.224)	0.146	(0.353)
Black	0.158	(0.365)	0.223	(0.416)	0.076	(0.265)	0.151	(0.358)
Asian	0.099	(0.299)	0.106	(0.308)	0.028	(0.165)	0.041	(0.198)
Mixed Race	0.109	(0.311)	0.141	(0.348)	0.039	(0.194)	0.077	(0.266)
Married	0.412	(0.492)	0.348	(0.5)	0.392	(0.5)	0.426	(0.495)
Age	29.5	(6.8)	29.2	(6.7)	28.6	(6.9)	29.0	(6.7)
Employment Rate								
All Women	0.668	(0.471)	0.639	(0.480)	0.682	(0.466)	0.668	(0.471)
Married Women	0.654	(0.476)	0.631	(0.482)	0.704	(0.456)	0.666	(0.472)
Single Women	0.677	(0.467)	0.643	(0.479)	0.668	(0.471)	0.670	(0.470)
Observations	94,216		164,663		180,793		2,470,392	

Panel B: Women potentially eligible for paid family leave policy take-up[a]

	New Jersey		NYC and PHL MSAs[b]		DE, NY, and PA[c]		All Other States[d]	
	Mean	(S. D.)	Mean	(S. D.)	Mean	(S. D.)	Mean	(S. D.)
Personal Attributes								
High School Degree	0.203	(0.402)	0.207	(0.405)	0.228	(0.420)	0.220	(0.414)
Some College	0.242	(0.428)	0.238	(0.426)	0.313	(0.464)	0.338	(0.473)
BA Degree or More	0.471	(0.499)	0.429	(0.495)	0.350	(0.477)	0.318	(0.466)
Hispanic	0.232	(0.422)	0.238	(0.426)	0.065	(0.247)	0.180	(0.385)
Black	0.129	(0.335)	0.194	(0.395)	0.078	(0.268)	0.139	(0.346)
Asian	0.123	(0.329)	0.105	(0.306)	0.029	(0.168)	0.045	(0.208)
Mixed Race	0.111	(0.314)	0.144	(0.351)	0.042	(0.201)	0.079	(0.269)
Married	0.769	(0.421)	0.728	(0.4)	0.703	(0.5)	0.712	(0.453)
Age	31.4	(5.0)	31.2	(5.3)	29.7	(5.2)	29.4	(5.4)
Employment Rate								
All Women	0.595	(0.491)	0.561	(0.496)	0.604	(0.489)	0.572	(0.495)
Married Women	0.600	(0.490)	0.572	(0.495)	0.616	(0.486)	0.572	(0.495)
Single Women	0.576	(0.494)	0.531	(0.499)	0.575	(0.494)	0.571	(0.495)
Observations	6,665		1,954		12,198		182,685	

[a] Eligibility is determined based on whether individual had a child in 2009 or later, the year of policy enaction.
[b] Includes people living in these MSAs in the states of New York and Pennsylvania.
[c] Includes people living in Delaware, New York, and Pennsylvania outside of the New York and Philadelphia MSAs.
[d] Includes people living in all states other than: California; Delaware; New Jersey; New York; and Pennsylvania.

Table 2.2
Linear probability model of employed last week – all women aged 18 to 40
(Standard errors clustered at PUMA level in parentheses)[a]

	Closest to NJ……….>…....…>…….….>………Furthest from NJ					
		NYC and PHL MSAs		DE, NY, and PA[b]		
	New Jersey	NJ Border PUMAs	Non-NJ Border PUMAs	< 60 miles from NJ	> 60 miles from NJ	All Other States
	(1)	(2)	(3)	(4)	(5)	(6)
Eligibility						
Currently Eligible:	0.0710***	0.0601***	0.0651***	0.0490**	0.0535***	0.0431***
Post 2009 x child under age 1	(0.0125)	(0.0154)	(0.0138)	(0.0220)	(0.0115)	(0.00275)
Col(1) - Col(X) Coef. [c]	-	[0.011]	[0.006]	[0.022]	[0.018]	[0.028**]
Eligible 1-3 years ago:	0.0684***	0.0397***	0.0491***	0.0249	0.0332***	0.0339***
Post 2009 x qualifying age[d]	(0.00999)	(0.0147)	(0.0101)	(0.0175)	(0.00845)	(0.00232)
Col(1) - Col(X) Coef. [c]	-	[0.029**]	[0.019*]	[0.044**]	[0.035***]	[0.035***]
Post 2009	-0.0285***	-0.0167	-0.0311*	-0.0855***	-0.0170***	-0.0736***
	(0.00585)	(0.0175)	(0.0183)	(0.0225)	(0.00599)	(0.02585)
Age of Youngest Child						
Under Age 1	-0.195***	-0.170***	-0.197***	-0.179***	-0.185***	-0.183***
	(0.0116)	(0.0131)	(0.0115)	(0.0202)	(0.00819)	(0.00236)
Age 1	-0.199***	-0.168***	-0.170***	-0.164***	-0.151***	-0.152***
	(0.0104)	(0.0164)	(0.00954)	(0.0161)	(0.00810)	(0.00261)
Age 2	-0.176***	-0.137***	-0.158***	-0.149***	-0.129***	-0.118***
	(0.0110)	(0.0173)	(0.0116)	(0.0162)	(0.00745)	(0.00243)
Age 3	-0.147***	-0.116***	-0.133***	-0.108***	-0.102***	-0.0958***
	(0.00917)	(0.0163)	(0.0108)	(0.0180)	(0.00844)	(0.00228)
Age 4 to 10	-0.0709***	-0.0487***	-0.0627***	-0.0373***	-0.0383***	-0.0307***
	(0.00738)	(0.0111)	(0.00885)	(0.0103)	(0.00446)	(0.00176)
Age 11 to 14	0.0138	0.0344***	0.0290***	0.0321**	0.0249***	0.0404***
	(0.00890)	(0.00972)	(0.00842)	(0.0137)	(0.00682)	(0.00184)
Age 15 to 18	0.0267*	0.0537***	0.0689***	0.0397**	0.0555***	0.0645***
	(0.0138)	(0.0177)	(0.0121)	(0.0171)	(0.00819)	(0.00227)
Other Controls						
High School Degree	0.139***	0.160***	0.147***	0.149***	0.190***	0.175***
	(0.00771)	(0.0123)	(0.00788)	(0.0113)	(0.00644)	(0.00172)
Some College	0.207***	0.230***	0.217***	0.219***	0.256***	0.253***
	(0.00965)	(0.0134)	(0.00839)	(0.0101)	(0.00815)	(0.00227)
BA Degree	0.309***	0.378***	0.347***	0.326***	0.377***	0.371***
	(0.00879)	(0.0147)	(0.00964)	(0.0112)	(0.00850)	(0.00266)
Hispanic	-0.00930	-0.0237***	-0.00661	-0.0408***	-0.0543***	-0.0079***
	(0.00575)	(0.00885)	(0.00715)	(0.0116)	(0.00801)	(0.00237)
Black	-0.0342***	-0.0249**	-0.00647	-0.0309**	-0.0691***	-0.0294***
	(0.00742)	(0.00957)	(0.00909)	(0.0147)	(0.00687)	(0.00205)
Asian	-0.124***	-0.0941***	-0.0920***	-0.164***	-0.192***	-0.0973***
	(0.00921)	(0.0115)	(0.00898)	(0.0191)	(0.0106)	(0.00320)

(Continues on next page…)

Table 2.2 (Continued)
Linear probability model of employed last week – all women aged 18 to 40
(Standard errors clustered at PUMA level in parentheses)[a]

	Closest to NJ……….>…....…>….…….>……….Furthest from NJ					
		NYC and PHL MSAs		DE, NY, and PA[b]		
	New Jersey	NJ Border PUMAs	Non-NJ Border PUMAs	< 60 miles from NJ	> 60 miles from NJ	All Other States
	(1)	(2)	(3)	(4)	(5)	(6)
Mixed Race	-0.00597	-0.00857	0.00179	-0.0318***	-0.0688***	-0.0272***
	(0.00653)	(0.00849)	(0.00697)	(0.00964)	(0.00946)	(0.00345)
Age	0.0879***	0.102***	0.107***	0.0766***	0.0677***	0.0694***
	(0.00427)	(0.00435)	(0.00367)	(0.00681)	(0.00375)	(0.00140)
Age Squared	-0.0013***	-0.0016***	-0.0016***	-0.0012***	-0.0010***	-0.0011***
	(6.74e-05)	(6.82e-05)	(5.95e-05)	(0.000109)	(6.11e-05)	(0.00002)
Married	-0.0621***	-0.0679***	-0.0701***	-0.0587***	-0.0609***	-0.0681***
	(0.00707)	(0.00677)	(0.00617)	(0.0102)	(0.00468)	(0.00163)
Married to Spouse With	0.0397***	0.0576***	0.0132*	0.0726***	0.0763***	0.0639***
High School Degree	(0.00644)	(0.00924)	(0.00726)	(0.0109)	(0.00467)	(0.00133)
Married to Spouse With	0.0395***	0.0601***	0.0300***	0.0848***	0.0904***	0.0700***
Some College	(0.00624)	(0.00862)	(0.00589)	(0.0111)	(0.00525)	(0.00148)
Married to Spouse With	-0.0437***	-0.0193***	-0.0272***	0.00995	0.0269***	-0.0163***
BA Degree	(0.00692)	(0.00657)	(0.00770)	(0.0108)	(0.00559)	(0.00164)
Constant	-0.788***	-1.089***	-1.108***	-0.603***	-0.544***	-0.524***
	(0.0636)	(0.0673)	(0.0539)	(0.0940)	(0.0537)	(0.0283)
State by Year Fixed Effects	8	16	16	24	16	368
Observations	94,216	59,026	105,637	37,412	143,381	2,470,392
R-squared	0.091	0.141	0.134	0.096	0.103	0.103
Employment Rate	66.8%	65.9%	62.9%	68.5%	68.1%	66.8%

[a] One * indicates significant at the 10 percent level; ** at 5 % level; *** at 1 % level.
[b] Does not include individuals in these three states residing in the New York and Philadelphia MSAs
[c] One-sided test of NJ coefficient larger than coefficient from other sample shown in [square brackets].
[d] Qualifying age means a child between 1 and 3 years old, born in 2009 or later.

Table 2.3
Linear probability model of employed last week – all men aged 18 to 40
(Standard errors clustered at PUMA level in parentheses)[a]

		Closest to NJ………..>…....…>….….….>……….Furthest from NJ				
		NYC and PHL MSAs		DE, NY, and PA[b]		
	New Jersey	NJ Border PUMAs	Non-NJ Border PUMAs	< 60 miles from NJ	> 60 miles from NJ	All Other States
	(1)	(2)	(3)	(4)	(5)	(6)
Currently Eligible:	0.0414***	0.0362***	0.0256***	0.0263	0.0570***	0.0444***
Post 2009 x child under age 1	(0.00970)	(0.0106)	(0.00937)	(0.0165)	(0.00843)	(0.00211)
Col(1) - Col(X) Coef. [c]	-	[0.005]	[0.016]	[0.015]	[-0.016]	[-0.003]
Eligible 1-3 years ago:	0.0422***	0.0511***	0.0148*	0.0414**	0.0466***	0.0483***
Post 2009 x qualifying age[d]	(0.00892)	(0.0110)	(0.00867)	(0.0156)	(0.00708)	(0.00197)
Col(1) - Col(X) Coef. [c]	-	[-0.009]	[0.027**]	[0.001]	[-0.004]	[-0.006]
Post 2009	-0.0357***	-0.0461***	-0.0390	-0.0851***	-0.0604***	-0.0261***
	(0.00607)	(0.0123)	(0.0274)	(0.0128)	(0.00819)	(0.00627)
State by Year Fixed Effects	8	16	16	24	16	368
Observations	91,079	53,697	99,368	37,105	145,293	2,399,305
R-squared	0.201	0.231	0.213	0.203	0.214	0.192
Employment Rate	75.2%	71.5%	72.5%	74.0%	71.4%	74.7%

[a] One * indicates significant at the 10 percent level; ** at 5 % level; *** at 1 % level. All models also include own attributes (education, race, age); spouse education level and youngest child age indicators.
[b] Does not include individuals in these three states residing in the New York and Philadelphia MSAs.
[c] One-sided test of NJ coefficient larger than coefficient from other sample shown in [square brackets].
[d] Qualifying age means a child between 1 and 3 years old, born in 2009 or later.

Table 2.4
Differential policy effects for women by marital status
(Standard errors clustered at PUMA level in parentheses)[a]

Panel A: Single Women

		Closest to NJ……….>….....…>….….….>……….Furthest from NJ				
		NYC and PHL MSAs		DE, NY, and PA[b]		
	New Jersey	NJ Border PUMAs	Non-NJ Border PUMAs	< 60 miles from NJ	> 60 miles from NJ	All Other States
	(1)	(2)	(3)	(4)	(5)	(6)
Currently Eligible:	-0.0327	0.0512	-0.00202	0.00662	0.0561**	0.0128**
Post 2009 x child under age 1	(0.0334)	(0.0337)	(0.0253)	(0.0424)	(0.0227)	(0.00512)
Col(1) - Col(X) Coef. [c]	-	[-0.084]	[-0.031]	[-0.039]	[-0.089]	[-0.046]
Eligible 1-3 years ago:	0.0159	-0.00606	0.0255	-0.000301	0.0189	0.00936**
Post 2009 x qualifying age[d]	(0.0201)	(0.0228)	(0.0217)	(0.0333)	(0.0162)	(0.00376)
Col(1) - Col(X) Coef. [c]	-	[0.022]	[-0.010]	[0.016]	[-0.003]	[0.007]
Post 2009	-0.0157**	-0.0245	-0.0373	-0.0932***	-0.0398***	-0.0253
	(0.00771)	(0.0200)	(0.0328)	(0.0279)	(0.00884)	(3.54)
State by Year Fixed Effects	8	16	16	24	16	368
Observations	52,350	38,785	64,171	21,260	81,656	1,325,369
R-squared	0.120	0.177	0.169	0.101	0.110	0.120
Employment Rate	67.7%	66.1%	63.5%	66.8%	65.9%	67.0%

Panel B: Married Women

		Closest to NJ……….>….....…>….….….>……….Furthest from NJ				
		NYC and PHL MSAs		DE, NY, and PA[b]		
	New Jersey	NJ Border PUMAs	Non-NJ Border PUMAs	< 60 miles from NJ	> 60 miles from NJ	All Other States
	(1)	(2)	(3)	(4)	(5)	(6)
Currently Eligible:	0.0678***	0.0373**	0.0559***	0.0295	0.0265**	0.0306***
Post 2009 x child under age 1	(0.0144)	(0.0171)	(0.0164)	(0.0236)	(0.0124)	(0.00292)
Col(1) - Col(X) Coef. [c]	-	[0.031*]	[0.012]	[0.038*]	[0.041**]	[0.037***]
Eligible 1-3 years ago:	0.0525***	0.0259	0.0283**	0.00276	0.0117	0.0182***
Post 2009 x qualifying age[d]	(0.0104)	(0.0163)	(0.0116)	(0.0215)	(0.00916)	(0.00236)
Col(1) - Col(X) Coef. [c]	-	[0.027*]	[0.024*]	[0.050**]	[0.041***]	[0.034***]
Post 2009	-0.0357***	-0.0111***	-0.00757**	0.0295***	-0.00826**	0.0373
	(0.00414)	(0.00241)	(0.00312)	(0.00676)	(0.00281)	(0.0356)
State by Year Fixed Effects	8	16	16	24	16	368
Observations	41,866	20,241	41,466	16,152	61,725	1,145,023
R-squared	0.071	0.094	0.102	0.102	0.100	0.100
Employment Rate	65.4%	65.5%	61.9%	70.7%	71.0%	66.6%

[a] One * indicates significant at the 10 percent level; ** at 5 % level; *** at 1 % level. All models also include own attributes (education, race, age); spouse education level and youngest child age indicators.
[b] Does not include individuals in these three states residing in the New York and Philadelphia MSAs.
[c] One-sided test of NJ coefficient larger than coefficient from other sample shown in [square brackets].
[d] Qualifying age means a child between 1 and 3 years old, born in 2009 or later.

Table 2.5
Persistence of policy effect on married women's employment
(Standard errors clustered at PUMA level in parentheses)[a]

		Closest to NJ………..>…......…>…..……….>……….Furthest from NJ				
		NYC and PHL MSAs		DE, NY, and PA[b]		
	New Jersey (1)	NJ Border PUMAs (2)	Non-NJ Border PUMAs (3)	< 60 miles from NJ (4)	> 60 miles from NJ (5)	All Other States (6)
Post 2009 x	0.0680***	0.0378**	0.0558***	0.0297	0.0263**	0.0306***
Child under age 1	(0.0144)	(0.0172)	(0.0164)	(0.0236)	(0.0124)	(0.00292)
Col(1) - Col(X) Coef. [c]	-	[0.030*]	[0.012]	[0.038*]	[0.042**]	[0.037***]
Post 2010 x	0.0658***	0.0477**	0.0188	0.0120	-0.00180	0.0160***
Youngest child age 1	(0.0141)	(0.0223)	(0.0165)	(0.0325)	(0.0118)	(0.00297)
Col(1) - Col(X) Coef. [c]	-	[0.018]	[0.047**]	[0.054**]	[0.068***]	[0.050***]
Post 2011 x	0.0362*	0.0149	0.0480***	-0.00708	0.0188	0.0226***
Youngest child age 2	(0.0186)	(0.0315)	(0.0165)	(0.0306)	(0.0148)	(0.00371)
Col(1) - Col(X) Coef. [c]	-	[0.021]	[-0.012]	[0.043]	[0.017]	[0.014]
Post 2012 x	0.0403*	-0.0309	0.0178	-0.00749	0.0446**	0.0167***
Youngest child age 3	(0.0236)	(0.0387)	(0.0214)	(0.0522)	(0.0226)	(0.00515)
Col(1) - Col(X) Coef. [c]	-	[0.071**]	[0.023]	[0.048]	[-0.004]	[0.024]
Age of Youngest Child						
Under age 1	-0.241***	-0.195***	-0.237***	-0.236***	-0.231***	-0.243***
	(0.0135)	(0.0134)	(0.0133)	(0.0226)	(0.00882)	(0.00229)
Age 1	-0.252***	-0.223***	-0.216***	-0.226***	-0.207***	-0.220***
	(0.0130)	(0.0165)	(0.0106)	(0.0206)	(0.00823)	(0.00271)
Age 2	-0.229***	-0.191***	-0.217***	-0.210***	-0.200***	-0.191***
	(0.0112)	(0.0197)	(0.0119)	(0.0174)	(0.00776)	(0.00265)
Age 3	-0.213***	-0.174***	-0.195***	-0.179***	-0.175***	-0.172***
	(0.0113)	(0.0206)	(0.0115)	(0.0224)	(0.0100)	(0.00270)
State by Year F.E.	8	16	16	24	16	368
Observations	41,866	20,241	41,466	16,152	61,725	1,145,023
R-squared	0.071	0.097	0.102	0.102	0.100	0.100
Employment Rate	65.4%	65.5%	61.9%	70.7%	71.0%	66.6%

[a] One * indicates significant at the 10 percent level; ** at 5 % level; *** at 1 % level. All models also include own attributes (education, race, age); spouse education level and youngest child age indicators.
[b] Does not include individuals in these three states residing in the New York and Philadelphia MSAs.
[c] One-sided test of NJ coefficient larger than coefficient from other sample shown in [square brackets].

Table 2.6
Differential policy effects by education level for married women
(Standard errors clustered at PUMA level in parentheses)[a]

		Closest to NJ……….>….....…>…….….…>……….Furthest from NJ				
		NYC and PHL MSAs		DE, NY, and PA[b]		
	New Jersey (1)	NJ Border PUMAs (2)	Non-NJ Border PUMAs (3)	< 60 miles from NJ (4)	> 60 miles from NJ (5)	All Other States (6)
Currently eligible x Less than HS	-0.0207 (0.0457)	0.0139 (0.0597)	-0.0215 (0.0375)	-0.0557 (0.0621)	-0.0109 (0.0355)	-0.0158** (0.00718)
Col(1) - Col(X) Coef.[c]	-	[-0.035]	[0.001]	[0.035]	[-0.010]	[-0.005]
Currently eligible x HS Degree	-0.0480 (0.0308)	0.101* (0.0521)	0.0128 (0.0296)	0.0479 (0.0424)	-0.0182 (0.0215)	-0.0121** (0.00569)
Col(1) - Col(X) Coef.[c]	-	[-0.149]	[-0.061]	[-0.096]	[-0.030]	[-0.036]
Currently eligible x Some College	0.0613** (0.0263)	-0.00416 (0.0381)	0.0260 (0.0261)	0.00955 (0.0333)	0.00593 (0.0194)	0.00956** (0.00449)
Col(1) - Col(X) Coef.[c]	-	[0.065*]	[0.035]	[0.052]	[0.055**]	[0.052**]
Currently eligible x BA Degree	0.0955*** (0.0184)	0.0363** (0.0170)	0.0896*** (0.0185)	0.0505 (0.0312)	0.0610*** (0.0151)	0.0631*** (0.00373)
Col(1) - Col(X) Coef.[c]	-	[0.059**]	[0.006]	[0.045]	[0.035*]	[0.032**]
Eligible 1-3 years ago x Less than HS	0.00703 (0.0473)	0.0448 (0.0530)	0.0459 (0.0282)	-0.0855* (0.0471)	-0.0658** (0.0265)	0.0168** (0.00753)
Col(1) - Col(X) Coef.[c]	-	[-0.038]	[-0.039]	[0.093]	[0.073*]	[-0.009]
Eligible 1-3 years ago x HS Degree	-0.00368 (0.0267)	-0.0300 (0.0352)	0.0253 (0.0269)	0.00939 (0.0490)	-0.0404** (0.0201)	-0.00294 (0.00518)
Col(1) - Col(X) Coef.[c]	-	[0.026]	[-0.029]	[-0.013]	[0.037]	[-0.001]
Eligible 1-3 years ago x Some College	0.00954 (0.0213)	0.0386 (0.0292)	-0.00122 (0.0218)	-0.0615* (0.0313)	-0.0180 (0.0162)	0.00685** (0.00345)
Col(1) - Col(X) Coef.[c]	-	[-0.029]	[0.011]	[0.071**]	[0.028]	[0.003]
Eligible 1-3 years ago x BA Degree	0.0840*** (0.0137)	0.0323 (0.0227)	0.0373** (0.0151)	0.0584* (0.0306)	0.0637*** (0.0117)	0.0327*** (0.00296)
Col(1) - Col(X) Coef.[c]	-	[0.052**]	[0.047**]	[0.026]	[0.020]	[0.051***]
Post 2009	-0.0467* (0.0242)	-0.0249 (0.0290)	0.000767 (0.0281)	0.00258 (0.0584)	-0.0294 (0.0191)	0.0067 (0.0380)
Post 2009 x HS Degree	-3.97e-05 (0.0254)	0.0441 (0.0308)	-0.00655 (0.0203)	0.0124 (0.0515)	0.0129 (0.0166)	-0.0023 (0.0040)
Post2009 x Some College	0.00761 (0.0233)	0.0275 (0.0297)	-0.0247 (0.0210)	0.0327 (0.0491)	0.0185 (0.0186)	0.0109*** (0.0040)
Post 2009 x BA Degree	0.0182 (0.0240)	0.0305 (0.0233)	-0.00552 (0.0206)	0.0358 (0.0490)	0.0327** (0.0160)	0.0327*** (0.0040)
State by Year F.E.	8	16	16	24	16	368
Observations	41,866	18,641	39,343	15,945	65,753	1,145,023
R-squared	0.073	0.096	0.104	0.100	0.099	0.101
Employment Rate	65.4%	65.5%	61.9%	70.7%	71.0%	66.6%

[a] One * indicates significant at the 10 percent level; ** at 5 % level; *** at 1 % level. All models also include own attributes (education, race, age); spouse education level and youngest child age indicators.
[b] Does not include individuals in these three states residing in the New York and Philadelphia MSAs.
[c] One-sided test of NJ coefficient larger than coefficient from other sample shown in [square brackets].

Table 2.7
Differential policy effects by spouse's education level for married women
(Standard errors clustered at PUMA level in parentheses)[a]

	Closest to NJ………..>…......…>….….….>……….Furthest from NJ					
		NYC and PHL MSAs		DE, NY, and PA[b]		
	New Jersey (1)	NJ Border PUMAs (2)	Non-NJ Border PUMAs (3)	< 60 miles from NJ (4)	> 60 miles from NJ (5)	All Other States (6)
Currently eligible x Spouse less than HS	0.0436 (0.0495)	-0.0687 (0.0677)	-6.53e-05 (0.0434)	-0.0666 (0.0603)	-0.0163 (0.0312)	-0.0260*** (0.0069)
Col(1) - Col(X) Coef. [c]	-	[0.112*]	[0.044]	[0.110]	[0.060]	[0.070**]
Currently eligible x Spouse HS degree	-0.00710 (0.0278)	0.0170 (0.0436)	0.000503 (0.0277)	0.00665 (0.0355)	0.0247 (0.0182)	0.0110** (0.0052)
Col(1) - Col(X) Coef. [c]	-	[-0.024]	[-0.008]	[-0.014]	[-0.032]	[-0.018]
Currently eligible x Spouse some college	0.0671*** (0.0255)	0.110*** (0.0317)	0.0658*** (0.0239)	0.108*** (0.0374)	0.0231 (0.0167)	0.0274*** (0.0045)
Col(1) - Col(X) Coef. [c]	-	[-0.043]	[0.001]	[-0.041]	[0.044*]	[0.040**]
Currently eligible x Spouse BA degree	0.0893*** (0.0171)	0.0261 (0.0185)	0.0753*** (0.0195)	0.00589 (0.0322)	0.0318* (0.0186)	0.0482*** (0.0037)
Col(1) - Col(X) Coef. [c]	-	[0.063**]	[0.014]	[0.083***]	[0.058**]	[0.041**]
Eligible 1-3 years ago x Spouse less than HS	-0.000905 (0.0485)	0.00510 (0.0511)	0.0372 (0.0321)	-0.109** (0.0474)	-0.0185 (0.0280)	0.0101 (0.0062)
Col(1) - Col(X) Coef. [c]	-	[-0.006]	[-0.038]	[0.11*]	[0.018]	[-0.011]
Eligible 1-3 years ago x Spouse HS degree	0.0173 (0.0235)	-0.0180 (0.0365)	0.0209 (0.0216)	-0.0423 (0.0300)	-0.00928 (0.0153)	0.0171*** (0.0045)
Col(1) - Col(X) Coef. [c]	-	[0.035]	[-0.004]	[0.060*]	[0.027]	[0.002]
Eligible 1-3 years ago x Spouse some college	0.0357* (0.0195)	0.0205 (0.0277)	0.0191 (0.0186)	0.00990 (0.0323)	-0.00728 (0.0158)	0.0154*** (0.0036)
Col(1) - Col(X) Coef. [c]	-	[0.015]	[0.017]	[0.026]	[0.043**]	[0.020]
Eligible 1-3 years ago x Spouse BA degree	0.0758*** (0.0138)	0.0378 (0.0247)	0.0296* (0.0157)	0.0690** (0.0340)	0.0358** (0.0144)	0.0161*** (0.0033)
Col(1) - Col(X) Coef. [c]	-	[0.038*]	[0.046**]	[0.007]	[0.040**]	[0.060***]
Post 2009	-0.0515** (0.0217)	0.00479 (0.0367)	0.0804** (0.0322)	0.0258 (0.0471)	-0.0786*** (0.0184)	0.0511*** (0.0060)
Post 2009 x Spouse HS degree	0.0145 (0.0236)	-0.00862 (0.0420)	-0.0147 (0.0191)	-0.0121 (0.0318)	0.0338** (0.0166)	-0.0105*** (0.0035)
Post 2009 x Spouse some college	-0.00401 (0.0234)	-0.0499 (0.0396)	-0.0327* (0.0177)	-0.00378 (0.0314)	0.0351* (0.0178)	0.0013 (0.0034)
Post 2009 x Spouse BA degree	0.0240 (0.0206)	-0.00405 (0.0338)	-0.00742 (0.0188)	-0.00170 (0.0309)	0.0627*** (0.0172)	0.0264*** (0.0034)
State by Year F.E.	8	16	16	24	16	368
Observations	41,866	18,641	39,343	15,945	65,753	1,145,023
R-squared	0.073	0.096	0.104	0.100	0.099	0.101
Employment Rate	65.4%	65.5%	61.9%	70.7%	71.0%	66.6%

[a] One * indicates significant at the 10 percent level; ** at 5 % level; *** at 1 % level. All models also include own attributes (education, race, age); spouse education level and youngest child age indicators.
[b] Does not include individuals in these three states residing in the New York and Philadelphia MSAs.
[c] One-sided test of NJ coefficient larger than coefficient from other sample shown in [square brackets].

Table 2.8
Comparison of married women with youngest child born in 2008 versus 2009
(Standard errors clustered at the PUMA level in parentheses)[a]

	Closest to NJ………..>…......…>……….….>……….Furthest from NJ					
		NYC and PHL MSAs		DE, NY, and PA[b]		
	New Jersey	NJ Border PUMAs	Non-NJ Border PUMAs	< 60 miles from NJ	> 60 miles from NJ	All Other States
	(1)	(2)	(3)	(4)	(5)	(6)
Policy eligible:	0.0407***	-0.00564	0.0310***	-0.00005	0.0124	0.0117***
Post '09 x Young child born '09	(0.00987)	(0.0195)	(0.0117)	(0.0164)	(0.00812)	(0.00223)
Col(1) - Col(X) Coef.[c]	-	[0.046***]	[0.010]	[0.041**]	[0.028**]	[0.029***]
Policy ineligible by one year:	-0.00749	-0.0216	0.00979	0.0310	0.0117	0.00655**
Post '09 x Young child born '08	(0.0125)	(0.0186)	(0.0123)	(0.0227)	(0.00996)	(0.00237)
Col(1) - Col(X) Coef.[c]	-	[0.014]	[-0.017]	[-0.038]	[-0.019]	[-0.014]
Post 2009	-0.0237***	-0.00598	0.00153	0.0540*	-0.0381***	0.105***
	(0.00900)	(0.0170)	(0.0218)	(0.0278)	(0.0119)	(0.0329)
Age of Youngest Child						
Under Age 1	-0.215***	-0.176***	-0.213***	-0.222***	-0.221***	-0.230***
	(0.0109)	(0.0117)	(0.00977)	(0.0219)	(0.00647)	(0.00181)
Age 1	-0.232***	-0.201***	-0.214***	-0.226***	-0.211***	-0.216***
	(0.0108)	(0.0150)	(0.0107)	(0.0189)	(0.00743)	(0.00235)
Age 2	-0.224***	-0.184***	-0.209***	-0.216***	-0.198***	-0.187***
	(0.0106)	(0.0171)	(0.0125)	(0.0168)	(0.00798)	(0.00242)
Age 3	-0.211***	-0.173***	-0.197***	-0.183***	-0.172***	-0.172***
	(0.0107)	(0.0177)	(0.0111)	(0.0215)	(0.00980)	(0.00254)
Age 4	-0.177***	-0.165***	-0.179***	-0.166***	-0.168***	-0.154***
	(0.0110)	(0.0213)	(0.0139)	(0.0165)	(0.00809)	(0.00264)
Age 5 to 10	-0.131***	-0.0976***	-0.120***	-0.0815***	-0.0879***	-0.0852***
	(0.0101)	(0.0142)	(0.0106)	(0.0117)	(0.00532)	(0.00233)
Age 11 to 14	-0.0483***	-0.0106	-0.0175	-0.0280*	-0.0235***	0.0143***
	(0.0119)	(0.0194)	(0.0126)	(0.0141)	(0.00797)	(0.00276)
Age 15 to 18	-0.0203	0.0153	0.0457**	0.0156	-0.00284	-0.0136***
	(0.0183)	(0.0306)	(0.0192)	(0.0208)	(0.00884)	(0.00228)
State by Year Fixed Effects	8	16	16	24	16	368
Observations	41,866	20,241	41,466	16,152	61,725	1,145,023
R-squared	0.066	0.092	0.098	0.101	0.098	0.100
Employment Rate	65.4%	65.5%	61.9%	70.7%	71.0%	66.6%

[a] One * indicates significant at the 10 percent level; ** at 5 % level; *** at 1 % level. All models also include own attributes (education, race, age); and spouse education level indicators.
[b] Does not include individuals in these three states residing in the New York and Philadelphia MSAs.
[c] One-sided test of NJ coefficient larger than coefficient from other sample shown in [square brackets].

Table 2.9
Analyzing potentially endogenous fertility decision's impact on policy effects for married women
(Standard errors clustered at PUMA level in parentheses)[a]

Panel A: Using actual youngest child status

		Closest to NJ………..>…....…>….….….>……….Furthest from NJ				
		NYC and PHL MSAs		DE, NY, and PA[b]		
	New Jersey	NJ Border PUMAs	Non-NJ Border PUMAs	< 60 miles from NJ	> 60 miles from NJ	All Other States
	(1)	(2)	(3)	(4)	(5)	(6)
Youngest Child Under Age 4	-0.173***	-0.161***	-0.168***	-0.180***	-0.160***	-0.168***
	(0.00709)	(0.0107)	(0.00679)	(0.0113)	(0.00572)	(0.00174)
Post 2009	-0.0400***	-0.0247	-0.00974	0.0367	-0.0424***	0.114***
	(0.00938)	(0.0178)	(0.0214)	(0.0286)	(0.0122)	(0.0332)
Post 2009 x Youngest Child Under Age 4	0.0488***	0.0327**	0.0417***	0.0349**	0.0191**	0.0234***
	(0.00908)	(0.0130)	(0.00893)	(0.0156)	(0.00744)	(0.00176)
Col(1) - Col(X) Coef.[c]	-	[0.016]	[0.007]	[0.014]	[0.030***]	[0.025***]
State by Year F.E.	8	16	16	24	16	368
Observations	41,866	20,241	41,466	16,152	61,725	1,145,023
R-squared	0.061	0.087	0.092	0.096	0.092	0.093
Employment Rate	67.7%	66.1%	63.5%	66.8%	65.9%	67.0%

Panel B: Using predicted youngest child status

		Closest to NJ………..>…....…>….….….>……….Furthest from NJ				
		NYC and PHL MSAs		DE, NY, and PA[b]		
	New Jersey	NJ Border PUMAs	Non-NJ Border PUMAs	< 60 miles from NJ	> 60 miles from NJ	All Other States
	(1)	(2)	(3)	(4)	(5)	(6)
Predicted Youngest Child Under Age 4[d]	-0.188***	-0.125**	-0.126**	-0.105**	-0.243***	-0.257***
	(0.0447)	(0.0501)	(0.0506)	(0.0412)	(0.0232)	(0.00587)
Post 2009	-0.0552***	-0.0367	0.0348	0.0815**	-0.0503***	-0.0172
	(0.0157)	(0.0220)	(0.0307)	(0.0352)	(0.0143)	(5.77)
Post 2009 x Predicted Young. Child Under Age 4	0.106***	0.0606	0.0422	-0.0921**	0.0420	0.0408***
	(0.0317)	(0.0440)	(0.0305)	(0.0443)	(0.0275)	(0.00579)
Col(1) - Col(X) Coef.[c]	-	[0.045]	[0.064*]	[0.20***]	[0.064*]	[0.065**]
State by Year F.E.	8	16	16	24	16	368
Observations	41,866	20,241	41,465	16,152	61,725	1,145,021
R-squared	0.038	0.065	0.071	0.069	0.071	0.071
Employment Rate	65.4%	65.5%	61.9%	70.7%	71.0%	66.6%

[a] One * indicates significant at the 10 percent level; ** at 5 % level; *** at 1 % level. All models also include own attributes (education, race, age); spouse education level indicators.
[b] Does not include individuals in these three states residing in the New York and Philadelphia MSAs.
[c] One-sided test of NJ coefficient larger than coefficient from other sample shown in [square brackets].
[d] Predicted youngest child under age 4 is the Year 2000 Census average probability of having a youngest child under the age of 4 for individuals of particular age*gender*marital status*education (4 cats.)*white race status combinations.

Chapter 3

Neighborhood Effects and the Decision of Women to Work

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3.1 Introduction

Neighborhood peer effects have been notoriously difficult to identify despite numerous attempts to do so in the literature. This has been true regardless of whether the focus is on crime, school performance, employment, or a variety of other important outcomes. Equally challenging has been to provide evidence of the mechanisms by which peer effects are transmitted. These difficulties arise in part because individuals may endogenously choose their residence so as to be close to peers, and also because peers themselves are often difficult to define a priori.[19] This paper makes progress on both fronts by drawing on a unique neighborhood cluster file in the 1985-1993 American Housing Survey (AHS) that follows groups of adjacent homes over time.[20] The geographic and panel features of the data enable us to rely on temporal variation in the attributes of target individuals and their immediate neighbors that is essential to identification of our models.

Our focus throughout is on whether women age 25 to 60 choose to work, and whether proximity to working and non-working peers and non-peers in adjacent homes affects that decision. For these purposes, an individual is said to work if they have positive earnings in the previous twelve months.[21] For women, this is an active choice which suggests that peer effects could be relevant. For men the decision to work as defined here is highly inelastic and for that reason, we expect peer effects to be small or absent. This enables us to use men as a placebo and falsification check on our model design.

[19] For recent reviews of the neighborhood and peer effects literature see Ioannides and Loury (2004), Granovetter (2005), Ioannides (2012), and Topa and Zenou (forthcoming). For a critical review of models and methods that have been used to analyze neighborhood effects see Gibbons et al (forthcoming).
[20] Few previous studies have taken advantage of the AHS neighborhood cluster files. Among those that have, Ioannides and Zabel (2003, 2008) also use the AHS cluster files to examine evidence of neighborhood effects. In their work the focus is on housing demand and home maintenance and relies on a very different identification strategy than here.
[21] We also perform all of our analysis defining the decision to work based on higher earnings thresholds, select results for which are presented in Appendix Table A-1 and are discussed briefly later in the paper.

Central to our approach, we assume that role model effects cause women to emulate the behavior of nearby peers regardless of whether those peers work or do not work. We also assume that word-of-mouth information about job opportunities is enhanced most by proximity to working peers, less so by proximity to working non-peers, and even less by proximity to non- working neighbors regardless of peer status.[22] These assumptions imply rank order restrictions on model coefficients associated with the impact of adjacent working and non-working peers and non-peers. Working peers should have the largest positive effect on a woman's propensity to work because of reinforcing effects of role models and information networks. Non-peers should have smaller effects regardless of their work status. Non-working peers should have the largest negative effect on a woman's decision to work because of the assumed dominant influence of role model effects. This structure helps us to identify evidence of peer effects and underlying mechanisms while also providing guidance for how to choose between alternate peer definitions.

As a benchmark, random assignment of neighbors as peers and non-peers would make the peer distinction meaningless which should cause the coefficients on proximity to peers and non-peers to be similar. On the other hand, peer classification schemes that effectively capture how peers are perceived should support the rank order of coefficients described above while maximizing the difference in coefficient values associated with working and non-working peers. We draw on these arguments to discriminate between alternative peer classification schemes. In all, we experiment with thirteen different peer definitions from broad to very refined. In all cases, peers are defined as individuals who share the same demographic traits as the target individual based on combinations of gender, age of children, education, and marital status.

[22] In related work, Calvo-Armengol and Jackson (2004) model the impact of a network of contacts on the employment outcomes of an individual. In their model agents are randomly presented with job offers which they can choose to take or pass them on to other network members. Therefore, the better your network is, in terms of better employment matches, the more likely it is information on job offers will be passed on to you.

Our most exacting peer definitions allow for up to thirty-six different types of people, only one of which is a peer for a given individual. For such refined classifications it seems unlikely that an individual would know whether a prospective adjacent neighbor was a peer before moving into a home. It is even less likely that an individual would choose a residence in anticipatation of a specific change in the peer and work status of adjacent neighbors. This, along with inclusion of person fixed effects and other controls, mitigates any possible endogenous sorting of individuals into neighborhood clusters. Moreover, the peer and work status of adjacent neighbors exhibits considerable temporal variation that is essential for estimation of the model. That variation arises from changes in the attributes of the target individual that affect a person's type (e.g. the birth of a child), changes in the attributes of neighbors who remain in the community between surveys, and in- and out-migration of neighbors from the cluster.

In our most robust models, when measuring proximity to working and non-working peers and non-peers we proxy for the actual work status of neighbors with peer-specific MSA-level employment rates for the survey year in question (in a manner to be clarified later in the paper). This eliminates possible effects of unobserved local labor demand shocks that would affect the work status of all neighborhood residents, and also simultaneous feedback between the work status of adjacent neighbors and the work status of the target individual. It also mitigates attenuation bias that would arise if a neighbor's current work status is misreported or not indicative of their usual activity. Importantly, instrumenting as above allows for the possibility that adjacent peers may provide valuable connections to a broader geographic community of working and non-working peers that affect an individual's work status.

Results from a variety of model specifications indicate that neighborhood peer effects influence a woman's decision to work and that this occurs at least in part because women emulate the work status of nearby role models. In this context, other women with similar age children appear to be most important as peers. Our most reliable estimates indicate that adding one additional working peer to a women's adjacent neighbors increases her tendency to work by 4.5 percentage points. Adding a non-working peer reduces her tendency to work by 9 percentage points. Adding working and non-working non-peers to a women's adjacent neighbors has little influence on her decision to work.

For men, simply specified models yield estimates of notable positive peer effects, contrary to our priors and suggestive of positive local labor demand shocks that affect employment throughout an individual's neighborhood cluster. Evidence of male peer effects disappears, however, when we proxy for neighbor work status using MSA-level peer- and non-peer specific employment rates. These patterns underscore the need to provide robust controls for localized time-varying labor demand shocks and also provide support for our research design.

Our identification strategy differs markedly from recent state-of-the-art efforts in the neighborhood and peer effects literature. One important class of studies, for example, draw on survey-based data that explicitly identify the structure of peer-based networks, as with friendship networks that document who is friends with who from among a group of individuals. Recent papers of this type include Bramoullé et al. (2009); Liu and Lee (2010), Calvó-Armengol et al. (2009), Lin (2010), Lee et al. (2010) and Liu et al. (2012). These studies typically draw on idiosyncratic features of the friendship network to identify peer effects, in conjunction with the use of the characteristics of friends of friends as instruments to tackle lurking concerns about endogenous membership in the network.[23]

[23] Additional studies of this type include Asphjell, Hensvik, and Nilsson (2013) who examine the timing of child bearing among women who work for the same employer, Cappellari and Tatsiramos (2010) who consider labor market outcomes among close friends, and Cingano and Rosolia (2012) who estimate reemployment rates among individuals displaced from the same company. All of these studies report evidence of peer and network effects.

A different approach is exemplified by two recent studies by Hellerstein *et al* (2011, 2014). These studies rely on confidential versions of the US LEHD employer-employee matched panel data that identify the individual as well as the identity of the employer. Residential and work place locations are reported at the census tract level. Using these data, Hellerstein *et al* (2014) control for person and employer fixed effects as well as census tract measures of proximity to co-workers in the residential community. Their results indicate that the presence of a larger number of co-workers in an individual's residential census tract is associated with reduced job turnover. Hellerstein *et al* (2014) interpret this as evidence of improved word-of-mouth labor market networks that result in better matches between employers and workers.[24]

A third recent approach to identification of neighborhood peer effects relies on experimental and pseudo experimental data in which individuals are randomly assigned to different neighborhoods. An example of the former includes Kling et al (2007) who analyze data from the Moving To Opportunity (MTO) experiment conducted in five U.S. cities by the US Department of Housing and Urban Development (HUD).[25] An example of the latter includes recent studies by Damm (2009, 2014) who evaluates the impact of random assignment of immigrants in Denmark into different neighborhoods around the country. Broadly speaking, a series of studies based on the MTO experiments have generally failed to find compelling evidence of neighborhood effects for most types of outcome measures (e.g. criminal activity, teen pregnancy, school achievement). Damm (2009, 2014), however, does find evidence that

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[24] In many respects, the Hellerstein *et al* (2011, 2014) papers build off of recent work by Bayer et al (2008). Bayer et al show that two individuals who live on the same census block are more likely to work together than if they live in the same group of roughly ten census blocks and that this pattern is even stronger among individuals of similar race and ethnicity. They interpret their results as evidence of word of mouth labor market network effects. Weinberg et al (2004) also uses detailed individual-level data from the NLSY to identify evidence of peer and network effects in labor markets.

[25] The program issued housing vouchers to participating low-income households, some of whome were issued Section 8 vouchers as a control group while the target group were randomly assigned to select neighborhoods (see http://portal.hud.gov/hudportal/HUD?src=/programdescription/mto for details).

proximity to employed individuals of one's own ethnicity increases the tendency for a recent immigrant to be employed. She interprets this as evidence of neighborhood-based word-of-mounth job networks that help immigrants secure employment.[26]

Relative to these and other studies, the data structure in the AHS neighborhood files is unique in that it follows hundreds of clusters of 8 to 12 adjacent homes over time. The extreme proximity of homes within a cluster along with the panel dimension allows us to achieve many of the advantages of random assignment data. On conceptual grounds and also based on diagnostic tests reported near the end of the paper, we argue that such temporal variation in proximity to peers is exogenous after conditioning on person fixed effects and more traditional controls.

Two important messages emerge from our study. First, women appear to be sensitive to role model effects of nearby peers when deciding whether to work. We believe this evidence is new to the literature while echoing recent work on cultural drivers of female labor supply (see Alesina et al. (2013) and surveys by Bertrand (2010) and Fernandez (2011)). Collectively, these studies draw on behaviorially-based arguments from sociology and psychology to argue that gender norms and attitudes are important drivers of heterogenous patterns of female labor supply across countries, ethnicities, and generations. An implication of that literature is that women's labor supply decisions are potentially sensitive to role model effects as we find here.[27]

[26] In related work, Beaman (2012) examines the labor market outcomes of political refugees assigned to communities across the United States. She finds that larger numbers of nearby recently assigned refugees hurts refugee labor market outcomes which she attributes to a competition effect. The presence of more established immigrants from the same country enhances refugee labor market outcomes, consistent with a positive labor market network effect.

[27] Several papers study the cultural component of trends in women's labor force participation, focusing on intergenerational transmission mechanisms (see for example, Fernandez (2011), Fernandez, Fogli and Olivetti (2004), Fogli and Veldkamp (2011). In particular, in the theoretical model proposed by Fogli and Veldkamp, women learn about the effects of maternal employment on children by observing nearby employed women. Their empirical investigation is based on county-level U.S. data from 1940-2000. They interpret the evidence of spatial autocorrelation in female participation rates as a diffusion of information about the role of nurture.

A second important message from our paper is that the AHS neighborhood cluster design is unique and valuable. Other data collection agencies should be encouraged to mirror that design, the key feature of which is to follow clusters of adjacent homes over time.

We proceed as follows. Section 2 describes the data. Section 3 outlines our conceptual model and identification strategy. Section 4 discusses summary measures and results, and Section 5 concludes.

3.2 Data

Data for the analysis are taken from the national core files and neighborhood supplement of the 1985, 1989, and 1993 waves of the American Housing Survey (AHS) panel. Each survey contains an extensive array of questions about the house, neighborhood, and occupants. The survey is designed to be approximately representative of the United States and yields a panel that is unique among major surveys in that it follows homes not people. The national core survey is conducted every odd year (e.g. 1985, 1987 ...) and collects data from occupants of roughly 55,000 homes. The neighborhood supplement survey was only conducted in 1985, 1989, and 1993, and targeted the 10 nearest neighbors of 680 AHS core houses, henceforth referred to as neighborhood clusters. The exact number of units surveyed varies across years because of budgetary and other considerations (see the Codebook for the AHS, April 2011 for details). As would be expected, few homes are present throughout the entire panel. Instead, homes enter and leave the survey at different times but not in manner that likely biases our results.[28]

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[28] The AHS is designed and implemented by the Department for Housing and Urban Development (HUD). Conversations with HUD officials confirmed that the composition of the AHS sample is adjusted over time to help ensure that it remains roughly representative of the U.S. For a succinct comparison of the sample design and coverage of the American Housing Survey (AHS), the American Community Survey (ACS), and the Current Population Survey (CPS) see http://www.census.gov/housing/homeownershipfactsheet.html. Additional details of the AHS sample design are provided in the codebook manuals listed in the reference section of this paper.
Ionannides and Zabel (2003) also provide detailed summary measures on the AHS cluster files.

Although the initial 1985 survey included 680 clusters, the overall neighborhood supplement sample ends up containing 737 different neighborhood clusters spread across 112 metropolitan statistical areas (MSAs). We restrict our estimating sample to adults between 25 and 60 years old which yields a sample of 13,743 individuals (see Table 3.1a). This excludes individuals who may not be working because they are either still in school or have retired.

As noted earlier, our primary estimating sample is further restricted to individuals who are present in at least two consecutive surveys *and* who are between ages 25 and 60 in *both* survey years. This reduces our estimating sample to 4,880 individuals and a total of 11,661 person-year observations (see Tables 3.1b and 3.1c). To be clear, it is this sample that is used to define our dependent variable. When measuring the average attributes of adjacent neighborhood peers and non-peers we use a similarly age-restricted sample but in this case include all individuals who are present in a given survey year regardless of whether the neighbor in question is present for one or multiple survey years. Our regression models also control for the percentage of adjacent neighbors that are over 18 years in age including those beyond age 60.

We define our dependent variable as 1 if the individual reports positive earned income in the previous year and 0 otherwise. We have also run our models using $5,000 (year-2013 dollars) as the cutoff to define work status. Results based on that specification are presented in the appendix (Table A3-1) for our most robust models and are similar to those in the main tables although evidence of peer effects among women is slightly weaker. As the earnings threshold is inceased beyond $5,000 results change in ways that are difficult to interpret because of the combined effects of three drivers of earnings: the decision to work, hours worked, and hourly wage (a proxy for skill). Only when we adopt a zero-earnings threshold do we isolate the decision to work. That decision is a meaningful choice for many women while a highly inelastic one for prime age men, a difference that we draw upon as discussed earlier. For these reasons we focus on the decision to work throughout the paper and use zero as the income threshold to define an individual's work status.

Finally, as discussed earlier, for parts of the analysis we replace a neighbor's actual work status with MSA level peer and non-peer employment rates for a given peer definition. In this context, individual types are based on a collection of demographic attributes that are used to define peer and non-peer neighbors; for example, a female with a high school degree, single, and with one child under age 5. MSA-level employment rates for all of the peer types used in the study are obtained from the Current Population Survey (CPS), March supplement for the years 1985, 1989, and 1993. In all cases, we measure employment rates in the CPS based on whether a given individual earned positive income in the previous year, mirroring our definition used for the AHS data.

3.3 Model and identification of peer effects

This section outlines our conceptual model and related testable hypotheses. We also describe the econometric specifications and identification strategy.

3.3.1 Conceptual framework and testable hypotheses

Consider a community populated with two sets of individuals, type A and type B. Individuals within each group view each other as peers and within each group some individuals work while others do not. Peers are assumed to share information on job market opportunities more readily than do non-peers and peers also serve as role models for each other, emulating each other's behavior. While this can also occur between non-peers we assume it does so to a lesser degree. Our goal in the empirical analysis to follow is to confirm whether peers and non-peers within a housing cluster affect individual work decisions, and to shed light on the underlying mechanisms by which this may occur.

Our regression models all contain variants of the following general expression,

$$work_{i,n} = \theta_1 WP_{i,n} + \theta_2 WNP_{i,n} + \theta_3 NWNP_{i,n} + \theta_4 NWP_{i,n} \tag{3.1}$$

where *work* equals 1 if individual *i* in neighborhood *n* works and 0 otherwise, *WP* is the number of nearby working peers, *WNP* is the number of nearby working non-peers, *NWNP* is the number of non-working non-peers, and *NWP* is the number of non-working peers. In viewing (3.1), suppose initially that individuals are randomly assigned to their neighborhoods and that the only systematic determinants of whether an individual works or does not work are the peer and non- peer variables in (3.1). Because information spillovers and role model effects both contribute to the positive effect of working peers on an individual's propensity to work, θ_1 should be especially large and positive. Information spillovers and role model effects may also contribute to a positive influence of working non-peers on an individual's propensity to work, but to a lesser degree. Regardless of peer status, non-working neighbors are expected to contribute relatively little information about job market opportunities. Proximity to non-working individuals also has a negative role model effect that is assumed to be especially strong for non- working peers. Summarizing, these modeling assumptions imply that,

$$\theta_1 > \theta_2 \geq 0 \geq \theta_3 > \theta_4 \tag{3.2}$$

The inequalities in (3.2) provide a set of testable relationships that are potentially revealing of neighborhood peer effects and of the mechanisms that contribute to those effects. Evidence, for example, that θ_4 is negative and more so than the other coefficients would be indicative of negative role model effects. That is because we assume that non-working peers have non-negative effects on an individual's access to information on job opportunities and that role model effects are stronger within as opposed to between peer groups. If θ_4 equals zero and θ_1 is positive and larger than the other coefficients, that would be consistent with the presence of word-of-mouth job market networks and related information spillovers as emphasized in Hellerstein *et al* (2014) and Damm (2014). If instead θ_4 is strongly negative and θ_1 is strongly positive (in the sense of the inequalities in (3.2)), then the positive coefficient on θ_1 would be consistent with the presence of positive peer effects arising from either information spillovers, role model effects, or both. To anticipate, estimates from our most robust models support the structure and inequalities in (3.2) when considering female labor supply.

3.3.2 *Empirical model*

Our challenge in testing the restrictions implied by (3.2) is to obtain consistent estimates of the peer and non-peer coefficients allowing for the influence of other drivers of whether an individual works and the possible endogenous sorting of individuals into their housing cluster. We begin by drawing on the panel feature of the data. For those homes that do not turn over between surveys we follow the individual occupants over time which enables us to include person fixed effects, δ_i. The fixed effects sweep out the influence of time-invariant individual and neighborhood cluster attributes. Additional time varying individual and cluster attributes are represented by the vectors $X_{i,t}$ and $X_{n,t}$, respectively, where t denotes the time period in question. Also included in the model are year fixed effects, δ_t, and controls for the MSA-level employment rate in a given survey year, $E_{t,n}$, the specific form for which differs depending on other features of the model (in a manner to be clarified later). Adding these controls to (3.1), our regression models are of the following general form,

$$work_{i,n,t} = \theta_1 WP_{i,n,t} + \theta_2 WNP_{i,n,t} + \theta_3 NWNP_{i,n,t} + \theta_4 NWP_{i,n,t} \quad (3.3)$$

$$+ b_1 X_{i,t} + b_2 X_{n,t} + \delta_i + \delta_t + E_{msa,t} + e_{i,n,t}$$

where the model error term $e_{i,n,t}$ captures the influence of any remaining unobserved time-varying, neighborhood-specific factors.

An important feature of (3.3) is that the peer and non-peer terms are individual level, neighborhood specific, time varying variables. Our primary threat to identification, therefore, is that time varying unobserved neighborhood specific factors may influence temporal variation in an individual's work status while also being correlated with temporal variation in proximity to working and non-working peers and non-peers. This could arise if proximity to nearby peers is endogenous, or because of the presence of unobserved local labor demand shocks, or because the work status of target and neighboring individuals simultaneously feedback on each other through (3.3). To clarify, suppose that peer effects do not exist in the sense that the true values for θ_1, θ_2, θ_3, and θ_4 are all zero. Suppose also that individuals choose their neighborhood to be close to peers and peers have similar unobserved tastes for work. Then this would bias upward the magnitude of the coefficients on the peer variables (θ_1 and θ_4) and would cause us to overstate evidence of peer effects. Alternatively, if individuals with a strong attachment to the workforce are drawn to neighborhoods with improving access to jobs, this would cause θ_1 and θ_2 to be positive and θ_3 and θ_4 to be negative. If these effects are more pronounced for peers then this would also cause us to mistakenly infer evidence of peer effects. Finally, simultaneous feedback between the work status of target individual and neighboring peers would bias upward the magnitude of the peer coefficients θ_1 and θ_4, also causing us to overstate evidence of peer effects. It is important, therefore, to control for possible endogenous temporal variation in both the peer and work status of neighbors within a given cluster.

Three features of our empirical design help to address such concerns. The first is the extreme proximity of neighbors in our data along with refined classifications of individuals into peer groups. The second is that in some models we rely on differencing to mitigate the influence of common unobserved factors. The third is that in our most robust models we proxy for the work behavior of adjacent peers and non-peers using MSA-level peer-specific employment rates. We comment further on each of these strategies below.

3.3.3 *Identification*

3.3.3.1 Neighbor proximity and classification of peers

If individuals do not choose their residence based on anticipated changes in the peer status of prospective neighbors that will help to ensure that temporal variation in proximity to peers and non-peers is exogenous. The manner in which we define peers along with the special features of the AHS neighborhood cluster panel help to ensure that is the case. Considering the data first, recall that the housing clusters are constructed from groups of adjacent homes in MSAs across the U.S. While individuals may know the demographic attributes of their broader community when choosing a residence, it is less likely that they would know whether prospective neighbors on a given block or in the house next door were peers or non-peers before moving into their home. It is even less likely that individuals would know of upcoming changes in the peer status of prospective neighbors when choosing their residence. This is especially true in our more refined models for which neighbors are classified into up to thirty-six different types, only one of which is coded as a peer.

In the empirical work to follow, we experiment with thirteen different definitions of peers. In all cases except one, for each target individual *i*, peers are defined as neighbors that share common demographic traits with *i* where the traits used for these purposes differ across peer definitions. The large number of peer definitions helps to establish robustness but also presents a challenge: how to choose a preferred classification scheme. On this we are guided by the following argument. At one extreme, suppose that neighborhood peer effects are present in the sense that the true model coefficients satisfy the inequalities in (3.2), but neighbors are randomly assigned as peers and non-peers. Then the peer and non-peer coefficients should be asymptotically similar which would imply an absence of peer effects. We begin with such a model as a base of reference. At the other extreme, suppose that we perfectly classify individuals as peers and non-peers. Given our strong priors that peers should have larger magnitude effects on an individual's work behavior than non-peers, accurate classification should maximize the difference between the peer and non-peer coefficients.

Regardless of the peer classification being used, recall that our target sample is always restricted to individuals between ages 25 and 60 to ensure that the decision of whether or not to work is relevant. Our simplest peer definition then classifies all individuals between ages 25 and 60 as peers and those outside of this group as non-peers. The next level of classifications require that peers share one additional trait. The first such model treats individuals of the same gender as peers. The second model defines individuals with at least one similar age child at home as peers based on three different categories: no children at home under age 18, at least one child at home under age 6, and at least one child at home between 6 and 18. Individuals with at least one child under age 6 and also at least one child between 6 and 18 are defined as peers for families with children in both age categories. The third model treats individuals of similar marital status as peers (married versus not married). The fourth model treats individuals as peers if they are of similar education status based on three categories, less than high school, high school or some college, and college degree or more. More refined definitions of peers interact two, three, and eventually all four of these classifications. Accordingly, our most refined classification scheme divides individuals into thirty-six different types: gender (2 groups) by age of children at home (3 groups) by marital status (2 groups) by education (3 groups).

It is worth emphasizing that as peer definitions become more refined exposure to peers among adjacent neighbors declines. For a broad definition such as age plus gender, for example, exposure is 34.4 percent for men and 39.0 percent for women (see Table 3.1c and the summary measures in Panels A and B of Table 3.3). For the most refined classification with 36 peer groups exposure is just above 8.5 percent for both men and women (see Table 3.4, column 7). Especially for these more refined models it is unlikely that an individual would know in advance if a prospective adjacent neighbor was a peer let alone whether the peer status of adjacent neighbors was about to change. For these reasons, we treat temporal variation in proximity to peers and non-peers as exogenous.

3.3.3.2 Differencing peer and non-peer effects

As emphasized above, it is also important to address possible unobserved local labor demand shocks. For that reason, in some of our models we use a differencing strategy under the assumption that this helps to difference away the influence of common unobserved time varying unobserved factors as with the arrival of a new nearby employer, for example. Specifically, we restrict $\theta_1 = -\theta_4$ and $\theta_2 = -\theta_3$ in expression (3.3). This implicitly assumes that working and non-working peers have similar magnitude but opposite signed effects on individual work behavior, as similarly for working and non-working non-peers. The regression model then becomes,

$$work_{i,n,t} = \theta_p(\mathrm{WPi}_{,n,t} - NWP_{i,n,t}) + \theta_{np}(\mathrm{WNP}_{\mathrm{i},n,t} - NWNP_{i,n,t}) \qquad (3.4)$$

$$+ b_1X_{i,t} + b_2X_{n,t} + \delta_i + \delta_t + E_{msa,t} + e_{i,n,t}$$

where θ_p and θ_{np} are the influence of peers and non-peers on an individual's work behavior. Under the further assumption that peers have a larger impact on individual work behavior than non-peers, evidence that $\theta_p > \theta_{np} \geq 0$ is consistent with the presence of peer effects.

The model in (3.4) has the advantage of differencing away common unobserved local time varying factors that might bias evidence of peer effects. A disadvantage of (3.4), however, is that it oversimplifies the relationship between peers and non-peers relative to the model in (3.3) causing us to lose our ability to shed light on underlying mechanisms (i.e. role model effects versus information spillovers). Differencing as in (3.4) also does not fully address the possible influence of local time varying labor demand shocks. As noted above, such shocks have potential to bias upward the magnitude of all of the peer and non-peer coefficients in expression (3.3), and therefore, the magnitude of θ_p and θ_{np} in (3.4). For these and other reasons we pursue yet another modeling strategy.

3.3.3.3 Proxying for neighbor work status

In our final and most robust modeling strategy, we proxy for a neighbor's actual work status using MSA-level peer-specific employment rates in a manner described below. We favor this strategy for several reasons. First, it eliminates the possibility that time varying localized labor demand shocks might contaminate estimates of the peer effect variables in the manner discussed above. Second, it eliminates possible simultaneous feedback between the work status of adjacent neighbors and the work status of the target individual. Third, it controls for the tendency of an individual to work and for that reason, helps to reduce attenuation bias that would arise if an individual neighbor's work status in a given year is misreported or not indicative of that neighbor's typical behavior. Fourth, and very different, adjacent peers may serve as a window into a community that extends well beyond the immediate housing cluster (as with school or religious groups, for example). It is plausible that access to that broader group could enhance word-of-mouth labor market networks and also further contribute to role model effects.

It is worth emphasizing that failing to allow for the first two effects above could result in upward biased estimates of peer effects while failing to address the latter two implies the opposite. For these reasons, we proxy for the actual work status of adjacent neighbors as follows. For a given peer definition, individual *i*'s neighbors in year *t* are divided into two groups, peers and non-peers. We proxy for the work behavior of neighboring peers using the year-*t* employment rate among individuals in *i*'s MSA that qualify as peers ($E_{i,P,msa,t}$). We proxy for the work behavior of neighboring non-peers in an analogous manner using the MSA-level employment rate for all non-peers combined ($E_{i,NP,msa,t}$).

Applying this strategy, expression (3.4) becomes,

$$\begin{aligned} work_{i,n,t} = {} & \theta_p[(E_{i,P,msa,t})P_{i,n,t} - (1-E_{i,P,msa,t})P_{i,n,t}] \\ & + \theta_{np}[(E_{i,NP,msa,t})NP_{i,n,t} - (1-E_{i,NP,msa,t})NP_{i,n,t}] \\ & + b_1X_{i,t} + b_2X_{n,t} + \delta_i + \delta_t + E_{msa,t} + e_{i,n,t} \end{aligned} \tag{3.5}$$

where the terms $P_{i,n,t}$ and $NP_{i,n,t}$ are the number of peers and non-peers from among adjacent neighbors and it should be emphasized that the overall MSA-level employment rate is retained as before. Observe also that identification in this model is based on differences in the expected number of adjacent working and non-working neighbors for both peers and non-peers since the bracketed terms simplify to $2(E_{i,P,msa,t})P_{i,n,t} - P_{i,n,t}$ and $2(E_{i,NP,msa,t})NP_{i,n,t} - NP_{i,n,t}$, respectively.

Proxying for neighbor work behavior in the same fashion in expression (3.3) gives,

$$\begin{aligned} work_{i,n,t} = {} & \theta_1(E_{i,P,msa,t})P_{i,n,t} + \theta_2(E_{i,NP,msa,t})NP_{i,n,t} \\ & + \theta_3(1-E_{i,NP,msa,t})NP_{i,n,t} + \theta_4(1-E_{i,P,msa,t})P_{i,n,t} \\ & + b_1X_{i,t} + b_2X_{n,t} + \delta_i + \delta_t + E_{msa,t} + e_{i,n,t} \end{aligned} \tag{3.6}$$

Looking ahead, we favor the specification in (3.6) because it addresses the four concerns highlighted above while retaining opportunities to provide evidence of peer effects as well as underlying mechanisms.

3.4 Results

3.4.1 Summary statistics

Table 3.1a reports summary statistics for all individuals that are present in at least one survey year while Table 3.1b reports analogous measures restricting the sample to individuals present in at least two survey years – the same sample as used in our estimation. Both tables present measures for individual education, number of children, marital status, and age, and also for their adjacent neighbors. An important point to note is that the summary measures are quite similar for the two samples although individuals present for two or more consecutive surveys (Table 3.1b) are somewhat more likely to be married.

An essential requirement for our models to be estimable is that there must be sufficient temporal variation in individual work status and also in the peer and non-peer variables. Table 3.1c provides evidence on this point for the sample of individuals present in two or more consecutive surveys. Notice that the upper panel in the table reports sample means for the levels of the *work* and peer/non-peer variables based on data pooled across survey years. The lower panel presents analogous measures for the change in these variables across adjacent surveys (four years apart).

Focusing first on our dependent variable, on average, 89 percent of men worked in the previous year while 69.7 percent of women worked. The standard deviation of the change in the *work* variable between adjacent surveys is 0.36 and 0.46 for men and women, respectively.

Importantly, in the lower panel, notice that 16.7 percent of men in the estimating sample (379 individuals) experience a change in work status between surveys, while for women the corresponding value is 26.5 percent (690 individuals). Without such variation it would not be possible to estimate our person fixed effect models.

Also present in Table 3.1c are summary measures based on the broadest peer definition (age between 25 and 60) and narrowest definition (gender by marital status by education by age of children at home). For the broad definition, roughly 8.5 neighbors are working peers, 0.95 neighbors are working non-peers, 2.5 neighbors are non-working non-peers, and 2.3 neighbors are non-working peers. Shifting to the narrow definition, exposure to peers declines sharply while exposure to non-peers increases by a corresponding amount. For both definitions the standard deviation of the change in the peer/non-peer variables between adjacent surveys indicates that there is notable temporal variation in these variables. That variation is also essential in order estimate the person fixed effect models.

3.4.2 Baseline regressions – no peer effects

Table 3.2 presents a baseline set of regressions that include individual and neighborhood cluster attributes but which omit the peer variables described earlier. Here and in all of the tables to follow the standard errors are clustered at the neighborhood cluster level. Columns 1 and 2 report results for men and women without person fixed effects. Columns 3 and 4 repeat the regressions but include the person fixed effects.

Results in Table 3.2 are consistent with priors and findings in the literature. In the first two columns, for example, notice that the tendency to work increases with an individual's level of education but much less so for men than for women. The smaller magnitude effect of education for men is consistent with the view that the decision to work for men is more inelastic. As anticipated, the presence of children at home has a notably negative influence on a woman's tendency to work as does being married; these attributes do not deter male propensity to work.

Not surprisingly, most of the individual and neighborhood cluster attribute coefficients become small and insignificant upon including person fixed effects in the models in columns 3 and 4. This is because several of these attributes exhibit little if any change between survey years and are therefore captured by the person fixed effects.[29] The exception is that children and marital status continue to have sharp negative effects on female propensity to work as seen in column 4 of the table.

3.4.3 Peer effects using actual neighbor work status

We next present estimates of the models in expressions (3.3) and (3.4) which allow for peer effects based on the actual work status of nearby peers and non-peers. We begin with the restricted model in (3.4) for which the influence of working and non-working peers is assumed to be of equal magnitude but opposite sign, and similarly so for non-peers. Results from this model are presented in Tables 3.3a and 3.3b for thirteen different peer definitions. In both tables, estimates for men are in Panel A while estimates for women are in Panel B.

In Table 3.3a, the first column in both panels is based on a random assignment of neighbors as peers and non-peers as a base of reference as described earlier. Notice that in both panels, the coefficients on non-peers in column 1 are larger than the coefficients on peers, opposite of what should occur in the presence of peer effects. The model in column 2 provides an alternate base of reference in that it treats all adjacent neighbors between ages 25 and 60 as peers while all other neighbors are non-peers. For men the coefficients on peers and non-peers are nearly identical and not significant, once again suggestive of an absence of peer effects. For women, the peer coefficient is positive and significant while the non-peer coefficient is essentially zero, indicating a possible presence of peer effects.

The remaining models in Table 3.3a enrich the definition of a peer. Column 3 further requires that a peer be of the same gender as the target individual in addition to being between

[29] It is for this reason that variables such as individual race and age are not included in the model. Race is time invariant while in the case of age, all individuals advance four years between surveys which is fully captured by the person fixed effects.

age 25 and 60. Column 4 substitutes marital status (married, not married) for gender when defining peers. Column 5 uses education which, as noted earlier, is broken into three categories: less than high school, high school or some college, and college degree or more. Column 6 uses age of children in the home based on whether there are no children present, at least one child under age 6, and at least one child age 6 to 18.

Several patterns are noteworthy in these later models. First, for both men and women, proximity to peers based on gender (column 3) is significantly and positively associated with an individual's tendency to work. Second, proximity to peers based on education (column 5) or the presence of similar age children (column 6) is significantly and positively associated with the tendency for women to work but not for men. Third, recall that we anticipate that $\theta_p > \theta_{np}$ in expression (3.4) and that accurate classification of neighbors as peers and non-peers should maximize the spread between θ_p and θ_{np}. Accordingly, 1-tailed tests of the difference between the peer and non-peer coefficients are presented in the middle of each panel for each of the models. For men, gender appears to be the most credible way of classifying adjacent neighbors as peers while for women, gender and age of children stand out. For women, these patterns will be recurring themes as we move to more robust specifications in the tables to follow.

Table 3.3b further enriches the definition of peers while maintaining the same general specification in expression (3.4). Columns 1-3 interact gender with marital status, education, and age of children, respectively. Column 4 interacts gender, marital status and education. Column 5 interacts gender, marital status, and age of children. Column 6 interacts gender, education, and age of children. Column 7 is the most refined peer definition and interacts gender, marital status, education, and age of children, which yields thirty-six different peer classifications as noted earlier.

The results in Panel A for men suggest that gender-education (column 2) is the most compelling manner in which to classify individuals as peers. For that specification, notice that the coefficient on peers indicates that adding 1 additional peer to the adjacent neighbors changes an individual's tendency to work by 1.17 percentage points while adding a non-peer has a much smaller effect of just 0.27 percentage points. There is intuitive appeal that men might be more likely to view other men of similar education as their primary peers. Nevertheless, it is also concerning that the peer effect coefficient is so large given our stong prior that for men the decision to work as defined here in this paper is highly inelastic. Moreover, the coefficient for men in column 2 is of similar magnitude to the corresponding coefficient for women in Panel B. This raises concerns about whether unobserved time varying labor demand shocks might be driving the peer effect coefficient for men. We will return to this point shortly. First, however, consider the patterns for women.

In Panel B of Table 3.3b (for women), the specifications in columns 3, 6 and 7 appear to maximize the difference between the coefficients for peers and non-peers. This suggests that gender, child status, and education together are most effective in defining how women view potential peers. Although the further influence of marital status in column 7 does increase the difference between θ_p and θ_{np} slightly relative to column 6, it is worth noting that in column 4 the difference between θ_p and θ_{np} is notably smaller and not significant when peers are defined based on gender, education and marital status. From these patterns we conclude that gender, child status, and education are important in defining peers for women but not marital status.

Focusing on column 6, the estimates imply that adding one additional peer to a woman's housing cluster will affect her work status by 1.4 percentage points. Adding one additional non-peer to the women's cluster affects her work status by only 0.15 percentage points. It is also worth noting that for the column 6 classification of peers (gender by child status by education), only 12 percent of a women's adjacent neighbors are peers as indicated in the summary measures at the bottom of Table 3.3b.

In Table 3.4 we next present estimates based on the model in expression (3.3) which continues to use the actual work behavior of neighbors to classify their work status but relaxes the coefficient restrictions imposed on (3.4). To conserve space, estimates are reported for just seven of the peer classifications and are ordered across columns as follows: (1) gender, (2) child status, (3) gender-education, (4) gender-child, (5) gender-education-marital status, (6) gender-education-child, and (7) gender-education-child-marital status. As before, estimates for men are in Panel A and for women in Panel B.

As a broad characterization, estimates for men yield limited evidence of peer effects. None of the models, for example, yield positive significant coefficients on nearby working peers and in some instances the coefficient has the wrong sign. On the other hand, several of the models yield sharp negative coefficients on non-working non-peers and peers. In column 5, for instance, the addition of one non-working peer to an individual's housing cluster is associated with a 4.1 percentage point decline in the likelihood that the individual works. Given previous arguments and other patterns in the table, we are concerned that this estimate may be driven primarily by localized time-varying labor demand shocks as might occur with the departure of a nearby employer, for example.

For women (Panel B), results are closer to our priors but still inconclusive. All of the working peer variables have positive but not significant coefficients. In addition, all of the non-working peer coefficients are negative but mostly also not significant. An exception is in column 2 which defines peers based on the age of children. In that instance, the coefficient suggests that the addition of one additional non-working peer to a women's housing cluster lowers her tendency to work by 1.6 percentage points. On the other hand, this estimate is close to the corresponding estimate for men in Panel A and for reasons described above that differs from our priors. We remain concerned, therefore, that the models in Table 3.4 (and Tables 3.3a and 3.3b) may not adequately allow for the combined effects of unobserved time varying labor demand shocks, simultaneous feedback, measurement error and a possible role for peers and non-peers beyond the immediate neighborhood cluster.

3.4.4 Peer effects using MSA-level peer and non-peer employment rates

We turn now to our most robust models which proxy for actual neighbor work status with peer-specific MSA-level employment rates as described earlier. As before, we begin with the restricted model, expression (3.5) in this case, and then follow with the unrestricted model based on expression (3.6). Estimates are presented in Tables 3.5a and 3.5b for the two specifications, respectively, for the same seven peer definitions as in Table 3.4. Once again, estimates for men are in Panel A and for women in Panel B.

Consider Panel A of Tables 3.5a and 3.5b first, for men. It is evident from the pattern of estimates that any evidence of peer effects has completely disappeared. In both tables, the coefficients are mostly small, always far from significant, and often of the wrong sign. This is evident in the negative coefficients on non-peers in the second row of Table 3.5a (WNP – NWNP) and the negative coefficients on working peers (WP) in the first row in Table 3.5b. The prevalence of small, insignificant coefficients is what should occur given the highly inelastic tendency for men to secure positive earnings over the course of a twelve month period.

A sharply different pattern is evident for women. Consider first Table 3.5a which presents estimates based on the restricted specification in expression (3.5). There is compelling evidence of peer effects based on the peer definitions in columns 3 and 6, gender-child and gender-education-child, respectively, echoing results from Table 3.3b. In column 6, for example, the difference in the peer and non-peer coefficients is 2.66 percentage points and significant. Based on this model, adding one additional peer to a woman's neighborhood cluster affects her propensity to work by 3.36 percentage points. Adding one additional non-peer affects work propensity by just 0.69 percentage points. Similar values are present in column 4 of Table 3.5a for the gender-child peer definition. Other peer definitions in the table yield notably muted evidence of peer effects.

Consider next Table 3.5b which presents estimates based on our more general specification in expression (3.6). Once again gender-child (column 4) and gender-child-education (column 6) appear to be the most compelling definitions of peers. For both of those specifications, the model estimates support the underlying theory described in expression (3.2) that $\theta_1 > \theta_2 \geq 0 \geq \theta_3 > \theta_4$. The negative and significant coefficient on non-working peers in these columns is especially informative. As argued earlier, while such individuals may not be a valuable source of information on job market opportunities, it seems unlikely that proximity to such individuals would impede access to information on potential jobs. On the other hand, the presence of such individuals would contribute to role model effects that would discourage a woman from choosing to work. For these reasons, we believe that the patterns in columns 4 and 6 provide unambiguous evidence that role model effects of nearby peers influence a woman's decision to work. Given this evidence, it is likely that role model effects also contribute to the positive coefficient on working peers in columns 4 and 6 but in that instance we cannot rule out a further effect arising from information spillovers that would contribute to word-of-mouth job market networks as emphasized in Hellerstein *et al* (2014) and Bayer et al (2008).

Table 3.6 presents a final extension in which we stratify the samples used in Panel B of Table 3.5b into single and married women, presented in Panels A and B of Table 3.6, respectively. It is worth noting that the point estimates in columns 4 and 6 for single women

(Panel A) and married women (Panel B) are similar both to each other and also to the estimates for the corresponding models in Table 3.5b. The estimates in Panels A and B of Table 3.6 are also noisier and less significant than in the corresponding models from Table 3.5b, but we believe that is primarily a result of having split the sample in half which reduces power. On balance, a close read of the patterns in Table 3.6 suggests that the evidence for peer effects based on proximity to women with similar age children and also of similar education status is similar for single and married women. For that reason, we view estimates from Table 3.5b, Panel B as most reliable given the combined and larger sample size.

3.4.5 Residual diagnostics and exogeneity

As emphasized throughout the paper, our ability to identify peer effects requires that temporal variation in the peer and non-peer variables is exogenous conditional on the various model controls. We provide here a set of residual-based diagnostic tests that help to reveal whether our models may violate such exogeneity conditions.[30] The intuition behind the test is to evaluate whether differences in unobserved factors that drive temporal variation in the work behavior of two individuals helps to explain whether those individuals live in the same neighborhood cluster. Evidence of correlation would be suggestive that unobserved location specific factors may affect neighborhood choice as well as the decision to work which could point to a potential violation of exogeneity.

To implement this test, all unique pairs of individuals used in a given $work$ regression are first determined. Each pair is then classified as neighbors if the two individuals live in the same neighborhood cluster in the same survey year. This is coded by setting $Neighbor_{i,j}$ to 1 for

[30] Goldsmith-Pinkham and Imbens (2013) suggest the use of a similar diagnostic procedure to investigate possible endogenous formation of networks in the context of a network model with peer effects. Patacchini and Venanzoni (2014) use a similar strategy to demonstrate the importance of network fixed effects in identifying peer effects in the demand for housing quality.

neighbors and 0 otherwise. For each pair we also calculate the absolute value of the difference in the observed attributes of the two individuals, denoted as $Dif\_X_{i,j}$, and the absolute value of the difference in their residuals from the *work* regression which we refer to as $Dif\_e_{i,j}$. Having formed these variables, we estimate a linear probability model with $Neighbor_{i,j}$ as the dependent variable and $Dif\_X_{i,j}$ and $Dif\_e_{i,j}$ as controls,

$$Neighbor_{i,j} = a_0 + a_1 Dif\_X_{i,j} + a_2 Dif\_e_{i,j} + c_{i,j} \tag{4.1}$$

where the coefficient of interest is a_2.

Estimates of expression (4.1) are presented in the appendix Tables A3-2a and A3-2b for each model in Tables 3.5a and 3.5b, respectively. Coefficients on $Dif\_e_{i,j}$ are also presented in Table 3.7 where they are normalized by dividing by the unconditional mean probability that two individuals live in the same neighborhood cluster (which equals 0.16 percent for men and 0.15 percent for women). The normalized coefficients in Table 3.7 should be interpreted as indicating the impact of a 1.0 unit difference in the *work* regression residuals for two individuals, equivalent to a 100 percentage point difference in their probability of working. It should also be noted that because there are several million individual-pair observations in a given regression, the power to detect small departures from zero is quite high.

Focusing on Table 3.7, notice that for men, regardless of the peer definition being used, a 1-unit increase in the difference in residuals is associated with a roughly 13 percent decrease in the probability that two individuals live in the same neighborhood cluster relative to the unconditional mean probability. This effect is small in economic terms but statistically significant as indicated by summary measures in the appendix tables (Tables A3-2a and A3-2b).

For women the test statistics are even smaller and not significant. The normalized coefficients in Table 3.7 suggest that a 1-unit increase in the difference in the residuals is associated with a roughly 3.5 percent decrease in the probability that two individuals live in the same cluster relative to the unconditional mean.

Along with the conceptual arguments and results described earlier, our inability to document notable significant correlation between differences in unobserved individual characteristics and neighborhood formation provides further support for the view that temporal variation in the peer and non-peer variables is exogenous conditional on person fixed effects and other model controls.

3.5 Conclusion

A host of policy and household decisions are based on belief that neighborhood peer effects are important. Nevertheless, peer effects have been notoriously difficult to identify as have the mechanisms by which they are transmitted. This paper makes progress on both fronts by drawing on a unique neighborhood cluster file in the 1985-1993 American Housing Survey (AHS) that follows groups of adjacent homes over time. The panel and refined geographic attributes of the data along with other features of our modelling design enable us to address difficult identification issues that have plagued this literature.

Our focus throughout has been on whether women work – defined as having positive earnings in the previous twelve months – and whether the work behavior of adjacent peers and non-peers affects that decision. Alternate model specifications indicate that for women, the combination of gender, age of children at home, and to a lesser degree education, are most important in defining peers. Results from our most robust specifications indicate that adding one additional working peer to a women's adjacent neighbors increases her tendency to work by 4.5 percentage points. Adding a non-working peer reduces her tendency to work by 9 percentage points. Adding non-peers to a women's adjacent neighbors has little influence on her decision to work. Importantly, our estimates also suggest that these effects arise at least in part because women emulate the work behavior of nearby peers. Placebo tests based on men yield little evidence of peer effects which is consistent with the view that for men the decision to work, and especially as defined here, is highly inelastic.

Our finding that peer definitions for women depend on the presence and age of children is consistent with recent work by Graves (2013), Compton and Pollak (2014) and Black *et al* (2014). Graves (2013) shows that school calendars affect female labor supply. Compton and Pollack (2014) show that women are more likely to work if they live near to the children's grandparents. Black *et al* (2014) show that women are more likely to work if they live in less congested metropolitan areas with shorter commute times. All three studies suggest the need for women to have viable child care if they are to work, either by relying on others (e.g. grandparents or schools) or because they can readily drive from work to home or a child's school if needed.

Our paper also reinforces an extensive literature on the importance of cultural norms as drivers of economic decisions and for the persistence of beliefs, norms, and socio-economic status across generations (Alesina and Giuliano (2010), Bisin and Verdier (2011)). While some studies argue that stagnation in women's labor force participation in the United States can be attributed at least in part to limited adoption of "family-friendly" policies (e.g. Blau and Kahn (2013)) our study confirms the importance of neighborhood-based cultural factors in shaping female labor market participation.

Finally, our results and modelling strategy highlight the value of refined geographically concentrated panel data when attempting to identify peer effects. Data collection agencies should be encouraged to adopt such sampling designs.

3.6 References

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Table 3.1a: Summary statistics stratified by gender and marital status (Samples include only adults aged 25 to 60 present in at least 1 survey)

	All Men Sample		All Women Sample		Married Women Sample		Single Women Sample	
Person-Specific Attributes								
	Mean	Std.Dev	Mean	Std.Dev	Mean	Std.Dev	Mean	Std.Dev
Education								
- Less than high school	0.137	0.343	0.155	0.362	0.142	0.349	0.184	0.388
- HS and some college	0.527	0.499	0.593	0.491	0.606	0.489	0.565	0.496
- BA degree or more	0.337	0.473	0.252	0.434	0.253	0.435	0.251	0.433
Child in HH	0.518	0.500	0.556	0.497	0.599	0.490	0.458	0.498
Married	0.762	0.426	0.693	0.461	1.000	0.000	0.000	0.000
Age	41.2	9.8	41.0	9.9	41.2	10.0	40.6	9.9
Average Attributes of Neighboring Adults Aged 25 to 60 Not Including Target Person [a]								
	Mean	Std.Dev	Mean	Std.Dev	Mean	Std.Dev	Mean	Std.Dev
Education								
- Less than high school	0.141	0.209	0.151	0.216	0.138	0.210	0.182	0.225
- HS and some college	0.562	0.250	0.562	0.246	0.562	0.246	0.561	0.245
- BA degree or more	0.298	0.268	0.287	0.266	0.300	0.265	0.257	0.267
Child in HH	0.510	0.277	0.527	0.276	0.548	0.257	0.481	0.309
Married	0.710	0.275	0.704	0.274	0.770	0.226	0.554	0.312
Age	41.1	5.3	41.2	5.4	41.8	5.3	39.9	5.4
Aged between 25 and 60 [b]	0.725	0.187	0.722	0.189	0.725	0.187	0.714	0.193
MSA level Attributes								
Employment Rate [c]	76.32%	3.57%	76.36%	3.57%	76.24%	3.54%	76.63%	3.62%
Number of neighborhoods	725		728		704		658	
Number of neigh*year clusters	1,988		2,019		1,845		1,525	
Number of adults in sample	6,470		7,273		4,901		2,569	
Number of observations	9,607		10,917		7,570		3,347	

[a] Average attributes of neighbors are calculated on a person level basis per year and are the average attributes of all the adults aged 25to 60 in the target person's neighborhood cluster that were surveyed in a particular year, not including the target person. The mean and std. dev. reported in the table above are the mean and standard deviation of these person-level "average attributes of neighbors" values for all the people belonging to a particular sample: (All Men, All Women, Single Women, and Married Women).

[b] Calculated for all adults aged 18 and over in the neighborhood in the particular year.

[c] Calculated using the Current Population Survey (CPS) which was obtained from www.ipums.org (King et al, 2010).

Table 3.1b: Summary statistics stratified by gender and marital status
(Samples include only adults present in 2 or more surveys age 25-60 in both surveys)

	All Men Sample		All Women Sample		Married Women Sample		Single Women Sample	
Person-Specific Attributes								
	Mean	Std.Dev	Mean	Std.Dev	Mean	Std.Dev	Mean	Std.Dev
Education								
- Less than high school	0.120	0.325	0.134	0.340	0.125	0.331	0.169	0.375
- HS and some college	0.528	0.499	0.614	0.487	0.622	0.485	0.568	0.496
- BA degree or more	0.351	0.477	0.253	0.435	0.253	0.435	0.264	0.441
Child in HH	0.555	0.497	0.559	0.497	0.599	0.490	0.413	0.493
Married	0.819	0.385	0.755	0.430	1.000	0.000	0.000	0.000
Age	43.4	8.8	43.1	9.0	43.1	8.9	43.7	8.9
Average Attributes of Neighboring Adults Aged 25 to 60 Not Including Target Person [a]								
	Mean	Std.Dev	Mean	Std.Dev	Mean	Std.Dev	Mean	Std.Dev
Education								
- Less than high school	0.124	0.196	0.138	0.205	0.123	0.199	0.181	0.217
- HS and some college	0.567	0.248	0.567	0.242	0.568	0.243	0.558	0.235
- BA degree or more	0.310	0.266	0.296	0.263	0.308	0.263	0.261	0.264
Child in HH	0.534	0.260	0.544	0.260	0.557	0.245	0.501	0.301
Married	0.765	0.241	0.750	0.248	0.802	0.202	0.585	0.304
Age	41.9	5.1	42.0	5.2	42.5	5.0	40.6	5.4
Aged between 25 and 60 [b]	0.725	0.184	0.722	0.184	0.724	0.183	0.716	0.189
MSA level Attributes								
Employment Rate [c]	76.47%	3.59%	76.49%	3.60%	76.40%	3.54%	76.80%	3.73%
Number of neighborhoods	630		653		557		371	
Number of neigh*year clusters	1,696		1,792		1,505		913	
Number of adults	2,272		2,608		1,908		603	
Number of observations	5,409		6,252		4,577		1,381	

[a] Average attributes of neighbors are calculated on a person level basis per year and are the average attributes of all the adults aged 25to 60 in the target person's neighborhood cluster that were surveyed in a particular year, not including the target person. The mean and std. dev. reported in the table above are the mean and standard deviation of these person-level "average attributes of neighbors" values for all the people belonging to a particular sample: (All Men, All Women, Single Women, and Married Women).

[b] Calculated for all adults aged 18 and over in the neighborhood in the particular year.

[c] Calculated using the Current Population Survey (CPS) which was obtained from www.ipums.org (King et al, 2010).

Table 3.1c: Summary statistics stratified by gender and marital status for employment and peer variables (Samples include only adults present in 2 or more surveys age 25-60 in both surveys)

	All Men Sample		All Women Sample		Married Women Sample		Single Women Sample	
Level based on pooled surveys	Mean	Std.Dev	Mean	Std.Dev	Mean	Std.Dev	Mean	Std.Dev
Work Last Year[a]	0.891	0.311	0.697	0.460	0.672	0.470	0.764	0.425
Peer Definition: Aged 25 to 60								
- Working Peers (WP)	8.671	3.421	8.438	3.455	8.817	3.355	7.180	3.508
- Working Non-Peers (WNP)	0.946	1.427	0.941	1.400	0.969	1.399	0.848	1.378
- Non-Working Non-Peers (NWNP)	2.677	2.295	2.674	2.317	2.775	2.350	2.400	2.232
- Non-Working Peers (WNP)	2.308	1.881	2.320	1.905	2.395	1.866	2.146	2.067
Peer Definition: Gender*Mar*Educ*Child Status								
- Working Peers (WP)	1.199	1.373	0.861	1.041	0.963	1.066	0.570	0.893
- Working Non-Peers (WNP)	8.335	3.169	8.454	3.224	8.763	2.985	7.374	3.704
- Non-Working Non-Peers (NWNP)	4.692	2.512	4.349	2.497	4.437	2.467	4.132	2.598
- Non-Working Peers (WNP)	0.134	0.406	0.431	0.796	0.508	0.846	0.215	0.597
Change between adjacent surveys	Mean	Std.Dev	Mean	Std.Dev	Mean	Std.Dev	Mean	Std.Dev
Work Last Year[a]	-0.024	0.364	0.002	0.456	0.001	0.479	-0.004	0.355
Percent that change work status	16.7%	-	26.5%	-	29.6%	-	15.9%	-
Number that change work status	379	-	690	-	565	-	96	-
Peer Definition: Aged 25 to 60								
- Working Peers (WP)	-0.249	2.549	-0.282	2.512	-0.332	2.522	-0.225	2.485
- Working Non-Peers (WNP)	0.018	1.716	-0.006	1.674	0.026	1.691	-0.113	1.626
- Non-Working Non-Peers (NWNP)	0.190	1.809	0.168	1.834	0.237	1.860	0.013	1.764
- Non-Working Peers (WNP)	-0.238	2.014	-0.231	1.998	-0.262	2.015	-0.101	1.971
Peer Definition: Gender*Mar*Educ*Child Status								
- Working Peers (WP)	-0.141	1.365	-0.069	1.099	-0.064	1.114	-0.032	0.928
- Working Non-Peers (WNP)	-0.108	2.711	-0.226	2.557	-0.242	2.528	-0.333	2.597
- Non-Working Non-Peers (NWNP)	-0.092	2.296	-0.045	2.326	0.003	2.313	-0.160	2.420
- Non-Working Peers (WNP)	-0.003	0.497	-0.094	0.844	-0.107	0.908	-0.023	0.548

[a] An individual is considered employed if they had any wage earnings in the previous year.

Table 3.2: Employment regressions – no peer effects[a]
(standard errors clustered at the neighborhood level in parentheses)

Estimation Sample	Men (1)	Women (2)	Men (3)	Women (4)
Individual Characteristics				
High school degree or some college	0.0735***	0.173***	0.00653	-0.0880
	(0.0199)	(0.0263)	(0.0723)	(0.0905)
College degree or more	0.0873***	0.291***	-0.0136	0.0190
	(0.0212)	(0.0283)	(0.0923)	(0.101)
At least one child < age 18 present at home	0.0259***	-0.0325**	-0.0109	-0.0450*
	(0.00990)	(0.0144)	(0.0199)	(0.0255)
Married	0.00248	-0.113***	0.0433	-0.121***
	(0.0136)	(0.0178)	(0.0314)	(0.0397)
Neighbor and MSA Characteristics[b]				
Percent High school degree or some college	0.0107	0.153***	-0.0910	0.0374
	(0.0338)	(0.0528)	(0.0766)	(0.0748)
Percent College degree or more	0.0198	0.0960*	-0.0964	-0.0124
	(0.0330)	(0.0520)	(0.0818)	(0.0952)
Percent age 25 to 60	0.0317	-0.0578	0.0267	-0.0148
	(0.0306)	(0.0428)	(0.0618)	(0.0723)
Percent with at least one child < 18 at home	0.0346	-0.0139	0.0345	0.0372
	(0.0218)	(0.0317)	(0.0410)	(0.0423)
Percent Married	-0.00474	0.0564	-0.0596	0.00868
	(0.0293)	(0.0384)	(0.0531)	(0.0513)
MSA employment rate [c]	0.197	0.0442	0.347	0.371
	(0.1600)	(0.2150)	(0.2890)	(0.3010)
Person Fixed Effects	-	-	2,272	2,608
Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	5,409	6,252	5,409	6,252
R-squared	0.013	0.058	0.587	0.700

[a] Sample includes only individuals age 25-60. Individuals are defined as working if they have positive earned income in the previous year. All models are estimated using the American Housing Survey neighborhood cluster file panel (1985-1993). One * indicates significant at the 10 percent level; two stars at the 5 percent level; and three stars at the 1 percent level.
[b] Calculated based on all working age (25 to 60 years old) neighbors, except for "Percent age 25 to 60" which is calculated based on all neighbors.
[c] Calculated using the Current Population Survey (CPS) which was obtained from www.ipums.org.

Table 3.3a: Restricted peer effect model with actual neighbor work status[a]
(standard errors clustered at the neighborhood level in parentheses)

PANEL A – MEN

Peer Group Definition	Random	All Ages 25-60	Gender	Married	Education	Child
	(1)	(2)	(3)	(4)	(5)	(6)
N working peer –	0.00257	0.00403	0.00964*	0.00486*	0.00462	0.00380
N non-wrk peer (WP - NWP)	(0.00255)	(0.00263)	(0.00502)	(0.00276)	(0.00340)	(0.00329)
N working non-peer -	0.00456*	0.00480	0.00167	0.00462	0.00354	0.00333
N non-wrk non-peer (WNP - NWNP)	(0.00276)	(0.00326)	(0.00253)	(0.00356)	(0.00286)	(0.00245)
[WP – NWP] – [WNP – NWNP]	-0.0020	0.0008	0.0080*	0.0002	0.0011	0.0005
(1-tail P-value)	(0.727)	(0.576)	(0.081)	(0.476)	(0.396)	(0.447)
Person Fixed Effects	2,272	2,272	2,272	2,272	2,272	2,272
% Neighbors that are Peers	50.0%	72.5%	34.4%	53.3%	38.9%	40.3%
Mean Peer Env	2.11	6.36	4.11	4.65	3.56	3.47
Mean Non-Peer Env	2.11	-1.73	1.13	1.11	1.74	1.99
R-square	0.587	0.588	0.588	0.588	0.587	0.587
Observations	5,409	5,409	5,409	5,409	5,409	5,409

PANEL B – WOMEN

Peer Group Definition	Random	All Ages 25-60	Gender	Married	Education	Child
	(1)	(2)	(3)	(4)	(5)	(6)
N working peer –	0.00127	0.00637**	0.00887**	0.00523	0.00720*	0.00633*
N non-wrk peer (WP - NWP)	(0.00292)	(0.00305)	(0.00383)	(0.00338)	(0.00399)	(0.00349)
N working non-peer -	0.00515	-0.000943	0.000744	0.00557	0.00146	-0.000416
N non-wrk non-peer (WNP - NWNP)	(0.00313)	(0.00381)	(0.00373)	(0.00373)	(0.00334)	(0.00339)
[WP – NWP] – [WNP – NWNP]	-0.0039	0.0073*	0.0081*	-0.0003	0.0057	0.0067*
(1-tail P-value)	(0.848)	(0.066)	(0.065)	(0.530)	(0.120)	(0.052)
Person Fixed Effects	2,608	2,608	2,608	2,608	2,608	2,608
% Neighbors that are Peers	50.0%	72.2%	39.0%	51.2%	39.1%	40.2%
Mean Peer Env	2.00	6.12	2.19	4.31	3.37	3.33
Mean Non-Peer Env	1.99	-1.73	3.34	1.19	1.73	1.91
R-square	0.700	0.701	0.701	0.701	0.701	0.701
Observations	6,252	6,252	6,252	6,252	6,252	6,252

[a] Sample includes only individuals age 25-60 in two consecutive surveys. One * indicates significant at the 10 percent level; two at 5 % level; three at 1 % level. All models also include: year fixed effects; MSA employment rate; individual education (less than HS; HS and some col.; and BA degree or more); child presence in HH; and marital status. As well as percent of neighbors aged 25 to 60 and their average: education (same 3 categories); marital status; and child in HH.

Table 3.3b: Restricted peer effect model with actual neighbor work status[a]
(standard errors clustered at the neighborhood level in parentheses)

PANEL A – MEN							
Peer Group Definition	Gen-Mar	Gen-Educ	Gen-Child	Gen Mar-Educ	Gen Mar-Child	Gen Ed-Child	Gen-Mar Ed-Child
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
N working peer – N non-wrk peer (WP - NWP)	0.00833 (0.00523)	0.0117** (0.00527)	0.00730 (0.00556)	0.00929* (0.00546)	0.00902 (0.00584)	0.00861 (0.00623)	0.00931 (0.00666)
N working non-peer - N non-wrk non-peer (WNP - NWNP)	0.00315 (0.00238)	0.00273 (0.00225)	0.00329 (0.00208)	0.00367* (0.00222)	0.00342* (0.00205)	0.00351* (0.00211)	0.00373* (0.00209)
[WP – NWP] – [WNP – NWNP] (1-tail P-value)	0.0052 (0.179)	0.0090** (0.046)	0.0040 (0.228)	0.0056 (0.150)	0.0056 (0.160)	0.0051 (0.198)	0.0056 (0.192)
Person Fixed Effects	2,272	2,272	2,272	2,272	2,272	2,272	2,272
% Neighbors that are Peers	26.1%	18.9%	19.2%	14.5%	15.2%	10.8%	8.7%
Mean Peer Env	3.17	2.30	2.26	1.81	1.82	1.30	1.06
Mean Non-Peer Env	1.92	2.54	2.66	2.99	3.01	3.44	3.64
R-square	0.588	0.588	0.588	0.588	0.588	0.588	0.588
Observations	5,409	5,409	5,409	5,409	5,409	5,409	5,409

PANEL B – WOMEN							
Peer Group Definition	Gen-Mar	Gen-Educ	Gen-Child	Gen Mar-Educ	Gen Mar-Child	Gen Ed-Child	Gen-Mar Ed-Child
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
N working peer – N non-wrk peer (WP - NWP)	0.00843* (0.00472)	0.0111** (0.00521)	0.0105** (0.00482)	0.0101 (0.00623)	0.0104* (0.00594)	0.0143** (0.00652)	0.0157** (0.00777)
N working non-peer - N non-wrk non-peer (WNP - NWNP)	0.00213 (0.00302)	0.00200 (0.00278)	0.000429 (0.00291)	0.00234 (0.00266)	0.00169 (0.00270)	0.00156 (0.00258)	0.00176 (0.00254)
[WP – NWP] – [WNP – NWNP] (1-tail P-value)	0.0063 (0.130)	0.0091* (0.057)	0.0101** (0.032)	0.0078 (0.123)	0.0087* (0.085)	0.0127** (0.029)	0.0139** (0.041)
Person Fixed Effects	2,608	2,608	2,608	2,608	2,608	2,608	2,608
% Neighbors that are Peers	27.2%	21.3%	21.8%	15.1%	15.3%	12.0%	8.6%
Mean Peer Env	1.41	1.23	1.19	0.80	0.76	0.65	0.43
Mean Non-Peer Env	3.66	3.65	3.77	3.89	3.95	3.99	4.10
R-square	0.701	0.701	0.701	0.701	0.701	0.701	0.701
Observations	6,252	6,252	6,252	6,252	6,252	6,252	6,252

[a] Sample includes only individuals age 25-60 in two consecutive surveys. One * indicates significant at the 10 percent level; two at 5 % level; three at 1 % level. All models also include: year fixed effects; MSA employment rate; individual education (less than HS; HS and some col.; and BA degree or more); child presence in HH; and marital status. As well as percent of neighbors aged 25 to 60 and their average: education (same 3 categories); marital status; and child in HH.

Table 3.4: Unrestricted peer effect model with actual neighbor work status[a] (standard errors clustered at the neighborhood level in parentheses)

PANEL A –MEN

Peer Group Definition	Gender	Child	Gen-Educ	Gen-Child	Gen Mar-Child	Gen Ed-Child	Gen-Mar Ed-Child
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
N working peer (WP)	0.00250	-0.00166	0.00626	-0.00270	-0.00205	0.00175	0.00104
	(0.00611)	(0.00408)	(0.00641)	(0.00535)	(0.00553)	(0.00639)	(0.00679)
N working non-peer (WNP)	-0.00500	-0.000848	-0.00425	-0.00172	-0.00161	-0.00162	-0.000860
	(0.00493)	(0.00378)	(0.00397)	(0.00354)	(0.00341)	(0.00360)	(0.00345)
N non-working non-peer (NWNP)	-0.00854	-0.00557	-0.0106**	-0.00667	-0.00631	-0.00870**	-0.00781*
	(0.00635)	(0.00413)	(0.00504)	(0.00444)	(0.00426)	(0.00436)	(0.00421)
N non-working peer (NWP)	-0.0205*	-0.0133*	-0.0195	-0.0325*	-0.0414**	-0.0259	-0.0369
	(0.0119)	(0.00777)	(0.0160)	(0.0170)	(0.0188)	(0.0220)	(0.0249)
Person Fixed Effects	2,272	2,272	2,272	2,272	2,272	2,272	2,272
% Neighbors that are Peers	34.4%	40.3%	18.9%	19.2%	15.2%	10.8%	8.7%
Mean WP	4.7	4.8	2.6	2.6	2.1	1.5	1.2
Mean WNP	4.4	4.4	6.8	6.8	7.4	8.0	8.3
Mean NWNP	3.3	2.4	4.2	4.2	4.4	4.6	4.7
Mean NWP	0.6	1.3	0.3	0.3	0.2	0.2	0.1
R-square	0.589	0.588	0.589	0.589	0.590	0.588	0.589
Observations	5,409	5,409	5,409	5,409	5,409	5,409	5,409

PANEL B –WOMEN

Peer Group Definition	Gender	Child	Gen-Educ	Gen-Child	Gen Mar-Child	Gen Ed-Child	Gen-Mar Ed-Child
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
N working peer (WP)	0.00925	0.00353	0.00784	0.00758	0.00309	0.0139	0.0116
	(0.00795)	(0.00576)	(0.00766)	(0.00744)	(0.00845)	(0.00922)	(0.0103)
N working non-peer (WNP)	-0.00429	-6.63e-05	0.000922	0.00141	0.00123	0.00239	0.00189
	(0.00774)	(0.00556)	(0.00555)	(0.00537)	(0.00524)	(0.00521)	(0.00528)
N non-working non-peer (NWNP)	-0.00723	0.00476	-0.00300	0.00109	-0.00162	-0.000557	-0.00142
	(0.00860)	(0.00596)	(0.00612)	(0.00579)	(0.00571)	(0.00561)	(0.00564)
N non-working peer (NWP)	-0.00790	-0.0164*	-0.0154	-0.0158	-0.0216*	-0.0155	-0.0222
	(0.00956)	(0.00876)	(0.0105)	(0.0103)	(0.0119)	(0.0121)	(0.0138)
Person Fixed Effects	2,608	2,608	2,608	2,608	2,608	2,608	2,608
% Neighbors that are Peers	39.0%	40.2%	21.3%	21.8%	15.3%	12.0%	8.6%
Mean WP	4.0	4.6	2.2	2.2	1.5	1.2	0.9
Mean WNP	5.0	4.3	7.0	7.0	7.7	8.1	8.5
Mean NWNP	1.6	2.4	3.3	3.2	3.8	4.1	4.3
Mean NWP	1.8	1.3	1.0	1.0	0.8	0.6	0.4
R-square	0.701	0.701	0.701	0.701	0.701	0.701	0.701
Observations	6,252	6,252	6,252	6,252	6,252	6,252	6,252

[a] Sample includes only individuals age 25-60 in two consecutive surveys. One * indicates significant at the 10 percent level; two at 5 % level; three at 1 % level. All models also include: year fixed effects; MSA employment rate; individual education (less than HS; HS and some col.; and BA degree or more); child presence in HH; and marital status. As well as percent of neighbors aged 25 to 60 and their average: education (same 3 categories); marital status; and child in HH.

Table 3.5a: Restricted peer effect model proxying for neighbor work status with MSA-level employment rates[a] (standard errors clustered at the neighborhood level in parentheses)

PANEL A – MEN

Peer Group Definition	Gender	Child	Gen-Educ	Gen-Child	Gen Mar-Child	Gen Ed-Child	Gen-Mar Ed-Child
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
N working peer – N non-wrk peer (WP - NWP)	-0.00556 (0.00875)	-0.00743 (0.00656)	0.00307 (0.00921)	-0.00839 (0.00797)	-0.00904 (0.00821)	-0.00321 (0.00877)	-0.00260 (0.00895)
N working non-peer - N non-wrk non-peer (WNP - NWNP)	-0.00502 (0.0152)	-0.00640 (0.00715)	-0.0129 (0.0109)	-0.00890 (0.0102)	-0.00807 (0.00894)	-0.00854 (0.00955)	-0.00602 (0.00872)
[WP – NWP] – [WNP – NWNP] (1-tail P-value)	0.0065 (0.513)	0.0006 (0.568)	0.0017 (0.108)	0.0022 (0.479)	0.0007 (0.542)	0.0008 (0.303)	-0.0002 (0.367)
Person Fixed Effects	2,272	2,272	2,272	2,272	2,272	2,272	2,272
% Neighbors that are Peers	34.4%	40.3%	18.9%	19.2%	15.2%	10.8%	8.7%
Mean Peer Env	3.49	3.12	2.02	1.95	1.61	1.15	0.97
Mean Non-Peer Env	1.34	2.28	2.77	3.01	3.35	3.64	3.84
R-square	0.587	0.587	0.587	0.587	0.587	0.587	0.588
Observations	5,409	5,409	5,409	5,409	5,409	5,409	5,409

PANEL B – WOMEN

Peer Group Definition	Gender	Child	Gen-Educ	Gen-Child	Gen Mar-Child	Gen Ed-Child	Gen-Mar Ed-Child
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
N working peer – N non-wrk peer (WP - NWP)	0.0197 (0.0168)	-0.000806 (0.0102)	0.0160 (0.0133)	0.0254* (0.0152)	0.0141 (0.0167)	0.0336** (0.0159)	0.0218 (0.0172)
N working non-peer - N non-wrk non-peer (WNP - NWNP)	-0.00478 (0.0137)	-0.00270 (0.0114)	0.00285 (0.0141)	0.00761 (0.0116)	0.00470 (0.0113)	0.00696 (0.0120)	0.00523 (0.0116)
[WP – NWP] – [WNP – NWNP] (1-tail P-value)	0.0245 (0.105)	0.0019 (0.402)	0.0132 (0.196)	0.0178* (0.090)	0.0094 (0.267)	0.0266** (0.040)	0.0166 (0.174)
Person Fixed Effects	2,608	2,608	2,608	2,608	2,608	2,608	2,608
% Neighbors that are Peers	39.0%	40.2%	21.3%	21.8%	15.3%	12.0%	8.6%
Mean Peer Env	2.28	3.06	1.35	1.19	0.79	0.71	0.48
Mean Non-Peer Env	3.14	2.24	3.36	3.63	3.80	3.85	4.01
R-square	0.700	0.700	0.700	0.701	0.700	0.701	0.700
Observations	6,252	6,252	6,252	6,252	6,252	6,252	6,252

[a] Sample includes only individuals age 25-60 in two consecutive surveys. One * indicates significant at the 10 percent level; two at 5 % level; three at 1 % level. All models also include: year fixed effects; MSA employment rate; individual education (less than HS; HS and some col.; and BA degree or more); child presence in HH; and marital status. As well as percent of neighbors aged 2s5 to 60 and their average: education (same 3 categories); marital status; and child in HH.

Table 3.5b: Unrestricted peer effect model proxying for neighbor work status with MSA-level employment rates[a] (standard errors clustered at the neighborhood level in parentheses)

PANEL A –MEN

Peer Group Definition	Gender	Child	Gen-Educ	Gen-Child	Gen Mar-Child	Gen Ed-Child	Gen-Mar Ed-Child
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
N working peer (WP)	-0.00655	-0.00288	0.000507	-0.00381	-0.00586	-0.00645	-0.00152
	(0.0121)	(0.0105)	(0.00921)	(0.0103)	(0.00988)	(0.0100)	(0.0106)
N working non-peer (WNP)	-0.00553	-0.00817	-0.0107	-0.00775	-0.00788	-0.00721	-0.00568
	(0.0158)	(0.00826)	(0.0114)	(0.0110)	(0.00937)	(0.0103)	(0.00935)
N non-working non-peer (NWNP)	0.000392	0.0116	0.00281	0.00607	0.00699	0.00395	0.00378
	(0.0212)	(0.0158)	(0.0178)	(0.0172)	(0.0148)	(0.0170)	(0.0152)
N non-working peer (NWP)	0.0154	-0.00742	0.00884	-0.0215	-0.0147	0.0252	-0.0114
	(0.0564)	(0.0319)	(0.0409)	(0.0458)	(0.0439)	(0.0473)	(0.0587)
Person Fixed Effects	2,272	2,272	2,272	2,272	2,272	2,272	2,272
% Neighbors that are Peers	34.4%	40.3%	18.9%	19.2%	15.2%	10.8%	8.7%
Mean WP	4.4	4.6	2.5	2.4	2.0	1.4	1.2
Mean WNP	4.7	4.8	7.1	7.2	7.8	8.3	8.6
Mean NWNP	3.4	2.5	4.3	4.2	4.4	4.7	4.8
Mean NWP	0.9	1.5	0.4	0.5	0.4	0.2	0.2
R-square	0.587	0.587	0.587	0.587	0.587	0.587	0.588
Observations	5,409	5,409	5,409	5,409	5,409	5,409	5,400

PANEL B –WOMEN

Peer Group Definition	Gender	Child	Gen-Educ	Gen-Child	Gen Mar-Child	Gen Ed-Child	Gen-Mar Ed-Child
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
N working peer (WP)	0.0311	0.0163	0.0238*	0.0444***	0.0256	0.0447***	0.0279
	(0.0209)	(0.0152)	(0.0141)	(0.0170)	(0.0176)	(0.0169)	(0.0183)
N working non-peer (WNP)	-0.000450	-0.0120	0.00231	-0.000490	-0.00459	0.000766	0.000203
	(0.0160)	(0.0127)	(0.0157)	(0.0124)	(0.0120)	(0.0127)	(0.0122)
N non-working non-peer (NWNP)	-0.00325	0.0328	-0.00138	0.00949	0.0140	0.00709	0.00651
	(0.0368)	(0.0226)	(0.0281)	(0.0236)	(0.0227)	(0.0224)	(0.0212)
N non-working peer (NWP)	-0.0591	-0.0496	-0.0551*	-0.0948***	-0.0650*	-0.0894***	-0.0590*
	(0.0450)	(0.0415)	(0.0308)	(0.0350)	(0.0339)	(0.0335)	(0.0356)
Person Fixed Effects	2,608	2,608	2,608	2,608	2,608	2,608	2,608
% Neighbors that are Peers	39.0%	40.2%	21.3%	21.8%	15.3%	12.0%	8.6%
Mean WP	4.0	4.5	2.2	2.2	1.5	1.2	0.9
Mean WNP	5.1	4.7	7.0	7.1	7.9	8.2	8.6
Mean NWNP	1.9	2.4	3.6	3.5	4.1	4.3	4.6
Mean NWP	1.7	1.4	0.9	1.0	0.8	0.5	0.4
R-square	0.700	0.701	0.701	0.702	0.701	0.702	0.701
Observations	6,252	6,252	6,252	6,252	6,252	6,252	6,252

[a] Sample includes only individuals age 25-60 in two consecutive surveys. One * indicates significant at the 10 percent level; two at 5 % level; three at 1 % level. All models also include: year fixed effects; MSA employment rate; individual education (less than HS; HS and some col.; and BA degree or more); child presence in HH; and marital status. As well as percent of neighbors aged 25 to 60 and their average: education (same 3 categories); marital status; and child in HH.

Table 3.6: Unrestricted peer effect model proxying for neighbor work status with MSA-level employment rates[a] (standard errors clustered at the neighborhood level in parentheses)

PANEL A –SINGLE WOMEN							
Peer Group Definition	Gender	Child	Gen-Educ	Gen-Child	Gen Mar-Child	Gen Ed-Child	Gen-Mar Ed-Child
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
N working peer (WP)	0.0130	-0.00162	0.0211	0.0217	0.0319	0.0292	0.0210
	(0.0337)	(0.0281)	(0.0203)	(0.0251)	(0.0310)	(0.0242)	(0.0286)
N working non-peer (WNP)	0.00155	-0.0291	-0.0179	-0.0157	-0.00884	-0.0134	-0.00457
	(0.0221)	(0.0229)	(0.0239)	(0.0214)	(0.0189)	(0.0182)	(0.0182)
N non-working non-peer (NWNP)	-0.0188	0.0769*	0.0190	0.0485	0.0176	0.0196	-0.00219
	(0.0632)	(0.0451)	(0.0440)	(0.0461)	(0.0378)	(0.0370)	(0.0348)
N non-working peer (NWP)	-0.0459	-0.0276	-0.0513	-0.0890*	-0.164*	-0.0722	-0.0871
	(0.0745)	(0.0748)	(0.0511)	(0.0516)	(0.0909)	(0.0505)	(0.0875)
Person Fixed Effects	603	603	603	603	603	603	603
% Neighbors that are Peers	41.2%	42.6%	22.0%	24.5%	12.9%	13.2%	7.1%
Mean WP	3.7	4.1	2.0	2.2	1.1	1.2	0.6
Mean WNP	4.2	3.7	6.2	5.9	7.2	7.1	7.8
Mean NWNP	1.6	1.8	3.1	2.8	3.7	3.7	4.1
Mean NWP	1.6	1.3	0.8	0.9	0.4	0.5	0.2
R-square	0.805	0.807	0.805	0.807	0.808	0.806	0.805
Observations	1,381	1,381	1,381	1,381	1,381	1,381	1,381

PANEL B – MARRIED WOMEN							
Peer Group Definition	Gender	Child	Gen-Educ	Gen-Child	Gen Mar-Child	Gen Ed-Child	Gen-Mar Ed-Child
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
N working peer (WP)	0.0381	0.0161	0.0199	0.0469**	0.0337	0.0385*	0.0280
	(0.0256)	(0.0189)	(0.0173)	(0.0226)	(0.0223)	(0.0218)	(0.0224)
N working non-peer (WNP)	0.00267	-0.0122	0.0127	0.00144	-0.00227	0.00579	0.00591
	(0.0198)	(0.0157)	(0.0192)	(0.0155)	(0.0158)	(0.0155)	(0.0155)
N non-working non-peer (NWNP)	-0.00886	0.0332	-0.0119	0.00605	0.0135	0.00391	0.00344
	(0.0423)	(0.0272)	(0.0337)	(0.0283)	(0.0280)	(0.0264)	(0.0264)
N non-working peer (NWP)	-0.0597	-0.0401	-0.0431	-0.0824*	-0.0567	-0.0630	-0.0406
	(0.0548)	(0.0519)	(0.0377)	(0.0467)	(0.0395)	(0.0449)	(0.0411)
Person Fixed Effects	1,908	1,908	1,908	1,908	1,908	1,908	1,908
% Neighbors that are Peers	38.3%	39.3%	21.1%	20.9%	16.3%	11.6%	9.2%
Mean WP	4.1	4.6	2.3	2.2	1.7	1.2	1.0
Mean WNP	5.3	5.0	7.3	7.5	8.1	8.5	8.9
Mean NWNP	2.0	2.6	3.8	3.7	4.2	4.5	4.7
Mean NWP	1.8	1.5	0.9	1.0	0.9	0.5	0.5
R-square	0.679	0.680	0.679	0.680	0.679	0.680	0.679
Observations	4,577	4,577	4,577	4,577	4,577	4,577	4,577

[a] Sample includes only individuals age 25-60 in two consecutive surveys. One * indicates significant at the 10 percent level; two at 5 % level; three at 1 % level. All models also include: year fixed effects; MSA employment rate; individual education (less than HS; HS and some col.; and BA degree or more); child presence in HH; and marital status. As well as percent of neighbors aged 25 to 60 and their average: education (same 3 categories); marital status; and child in HH.

Table 3.7: Percent change in the probability that two individuals live in the same neighborhood cluster (relative to the unconditional probability) in response to a 1-unit (100 percentage point) difference in their *Work* regression residuals

	Gender	Child	Gen-Educ	Gen-Child	Gen Mar-Child	Gen Ed-Child	Gen-Mar Ed-Child
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
MEN							
Table 3.5a Models[a]	-13.17%**	-12.47%**	-12.98%**	-13.10%**	-13.04%**	-12.85%**	-13.04%**
Table 3.5b Models[a]	-13.17%**	-12.54%**	-13.17%**	-13.29%**	-13.23%**	-12.79%**	-13.17%**
WOMEN							
Table 3.5a Models[a]	-4.57%	-3.32%	-3.58%	-3.98%	-3.58%	-3.70%	-3.41%
Table 3.5b Models[a]	-4.92%	-4.22%	-3.93%	-5.33%	-4.41%	-4.73%	-3.83%

[a] One * indicates significant at the 10 percent level; two at 5 % level; three at 1 % level. The reported coefficients are equal to the raw coefficients reported in Appendix Tables A3-2a (for the Table 3.5a models) and A3-2b (for the Table 3.5b models) normalized by the unconditional sample probability that two individuals are in the same neighborhood cluster. For men the unconditional probability is 0.0016 (0.16 percent). For women the unconditional probability is 0.0015 (0.15 percent).

Chapter 4

Unemployment Risk and the Demand for Home Equity Lines of Credit

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4.1 Introduction

This paper analyzes how the frequency and predictability of facing spells of unemployment impacts households' demand for home equity loans or lines of credit (HELOC). Using American Community Survey 2003-2013 data, I find household heads under age 60 whose occupational unemployment rates are significantly impacted by quarter-on-quarter changes in GDP, or business cycle effects, are more likely to secure a HELOC. Results also indicate household heads under age 40 facing seasonality in occupational employment, as measured by the difference between the highest and lowest unemployment monthly factors, tend to hold such home equity withdrawal devices. Overall, results point towards consumption smoothing motives influencing the decision to secure a HELOC.

For younger households, evidence of the demand for securing a HELOC being influenced by seasonality or business cycle driven fluctuations in occupational employment is strongest when coupled with house price appreciation. The literature has shown us that younger households are more likely to be credit constrained (see Haurin, Herbert and Rosenthal, 2007). Accordingly, for younger households house price increases are larger drivers of home equity withdrawal behavior (*e.g.* Mian and Sufi, 2011; Yamashita, 2007). Under the assumption that house price appreciation more significantly impacts the supply of HELOCs than demand, such shifts in supply allow one to trace out the demand curves for workers with different employment characteristics. This enables a cleaner identification of how the various measures of unemployment risk and seasonality impact younger households' demand for HELOCs.

Authors have cautioned against the use of occupation-specific measures of employment risk due biases resulting from the fact that people's level of risk aversion (Lusardi, 1997) or access to credit (Bernhardt and Backus, 1990) may factor into occupational choice. To address such concerns this paper uses the idea borne in Shore and Sinai (2010) that same-occupation couples face a higher correlation in unemployment shocks than do different-occupation ones. Specifically, the estimated spousal correlation in occupation-specific unemployment rates is used to split two-worker households into three groups: those with negative or zero correlation; those with a weakly positive correlation; and those with a strong positive correlation.

Results show households with a strong positive spousal correlation are more likely to secure access to HELOCs when facing seasonality and business cycle induced fluctuations in employment. This reflects their lesser ability to use spousal income as an alternative method for smoothing consumption relative to lower spousal unemployment correlation couples. Under the assumption that spouse choice is not influenced by risk aversion and access to credit, this method shows how couples with an arguably exogenously higher risk of facing joint spells of unemployment respond more to employment variance in their decision to hold a HELOC.

To my knowledge, looking specifically at the use of home equity loans and lines of credit as devices for tapping into stored home equity when facing unemployment risk is novel in the literature.[31] My prior is that these devices may be particularly useful in smoothing out small shocks to consumption resulting from breaks in employment due to them being a relatively low-cost manner for drawing upon stored home equity. This is likely to be the case when compared to alternatives such as cash-out mortgage refinancing or selling the home to extract stored equity. Once set up, a HELOC may be repeatedly drawn upon as needs arise so individuals facing frequent and predictable shocks to employment are more likely to favor this option for tapping into stored home equity. The conceptual model laid out in Section III details why this may be the case. HELOCs may also be favored over alternative short-term credit solutions such as credit

[31] Duca and Kumar (2014) use Health and Retirement Study data to assess how financial literacy impacts people's likelihood of extracting home equity via home equity loans, in a permanent income hypothesis framework. They show that the financially literate are more likely to withdraw equity via home equity loans.

cards and personal loans because they tend to charge lower interest rates since the home serves as collateral for the lender.

Figure 4.1 displays the age profile of households' probability of holding a first mortgage as well as the probability of holding second-lien loans for those also holding primary mortgages. In the ACS only individuals who hold a primary mortgage are asked questions regarding their holdings of secondary mortgages and home equity loans of lines of credit. It is also important to note the data does not enable one to distinguish whether households hold a home equity loan or a home equity line of credit. Figure 4.1 shows the probability of holding a HELOC peaks around age 50, significantly later than that of holding primary or secondary mortgages.[32] This is consistent with mortgages being paid off as age increases, and with older households generally having more home equity which they can access using HELOCs.

The data restriction pertaining to being unable to know HELOC status for non-primary mortgage holding households is likely to be least taxing for households between the ages of 22 to 52, for whom at least 80% of homeowners hold a primary mortgage. Since results regarding the responsiveness of HELOC demand to employment seasonality and business cycle driven fluctuations are strongest for these younger homeowner groups, this further supports the validity of the findings.

Given that this paper is analyzing home equity withdrawals during a period of particularly striking developments in the housing market, namely the lead up to and period after the hosing bubble burst in 2007. It is important to understand what the role of home equity loans and lines of credit may have been in these events.

[32] This is consistent with Agarwal, Driscoll, Gabaix, and Laibson (2007); who find annual percentage rates (APRs) charged on HEL and HELOCs are U-shaped with respect to age, with a minimum value around age 50.

Bernstein (2008) shows that between 2001 and 2007, home equity lines of credit were increasingly used by new mortgagees in order to reduce their loan-to-value ratios on their first mortgage and therefore avoid having to take out primary mortgage insurance. Lee, Mayer, and Tracy (2012) similarly report the use of home equity lines of credit to avoid large down payments at mortgage origination. LaCour-Little, Yu, and Sun (2014) show that home equity lines of credit during this period were commonly used to finance the purchase of non-owner-occupied properties. Eriksen, Kau, and Keenan (2013) estimate that from 2004 to 2008 12.6% of newly originated mortgages included second-lien loans. They find that borrowers with second-lien loans were significantly more likely to default on their loans. Similar results regarding higher default probabilities among mortgagees with second-lien loans are found by LaCour-Little, Calhoun, and Yu (2011).

The work in the preceding paragraph shows the probability of securing home equity loans in this period increased dramatically for reasons unrelated to any consumption smoothing motives. This is why the inclusion of state by year fixed effects is vital for the identification of how the frequency and predictability of unemployment spells may influence the demand for HELOCs.

The idea that individuals will make use of savings to hedge against income shocks has long been a topic of interest in the economics literature, dating back to the permanent income hypothesis of Friedman (1957) and Modigliani and Brumberg's (1954) life-cycle hypothesis. Several authors have looked at evidence of households using home equity as a consumption smoothing tool.

Carroll, Dynan and Krane (2003) look at variation in a household's wealth holdings in the Survey of Consumer Finances as a function of uncertainty regarding employment.

Employment uncertainty is estimated by the probability of being unemployed for households of similar characteristics in the Current Population Survey. The authors find evidence that increased job loss risk increases wealth holdings, consistent with a precautionary savings motive. No such results are found if excluding home equity from wealth calculations, indicative of the fact that home equity can be an important tool for consumption smoothing. They do not specifically address whether home equity loans and lines of credit are the mechanisms used to tap into that stored home equity; unlike the analysis herein.

This same idea is borne out in the work of Davidoff (2006), Shore and Sinai (2010), and Benjamin and Chinloy (2008). Davidoff (2006) shows there is evidence of precautionary savings in home purchasing decisions. He does so by finding that households whose income is highly correlated with house prices are less likely to own a home and that, when they do own, they on average have lower levels of home investment than other households. Benjamin and Chinloy (2008) develop a theoretical model where representative households have two “piggybanks” to accumulate wealth in, housing and retirement accounts. Their model shows that individuals will tap into these stores of wealth when facing shocks to income by borrowing on their home equity through: increasing mortgage debt; re-financing; or drawing on home equity lines of credit.

Shore and Sinai (2010) analyze how consumption of housing is affected by employment risk by comparing housing consumption for two-worker households where both workers have the same occupation versus ones with different occupations. They find evidence that among workers who face high housing adjustment costs (owners), same occupation couples spend 2.1% more on housing than other couples; no such difference is evident when workers face low housing adjustment costs (renters).

The precautionary savings motivation for housing consumption has also been investigated for other countries. Evidence of such behavior has been found for homeowners in Germany and Spain (Diaz-Serrano, 2005) and Japan (Moriizumi and Naoi, 2011). Other authors have looked at consumption smoothing motives driving overall levels of home equity withdrawals in other countries (*e.g.* Ebner, 2013; Shwartz *et al*, 2008; and Wood *et al*, 2003). Consumption smoothing motives impacting the decision to carry out a mortgage refinancing behavior (*e.g.* Angelini and Simmons, 2005; Benito, 2009; and Hurst and Stafford, 2004) or take out a second mortgage (Manchester and Poterba, 1989) has also been addressed in the literature.

The remainder of the paper proceeds as follows: Section II describes the data used in the analysis; Section III details the conceptual model and identification strategy; Section IV discusses the empirical results; and Section V provides a conclusion.

4.2 Data and Summary Statistics

Data for the analysis is obtained from the American Community Survey (ACS), from 2003 to 2013, and from the 1993 to 2002 monthly Current Population Surveys (CPS) obtained via the IPUMS-USA website (Ruggles *et al*, 2010). The ACS dataset contains information on a series of socio-demographic characteristics of surveyed individuals as well as providing information regarding their home ownership status and mortgaging activity. Table 4.1 presents the summary statistics for the variables used in the analysis for each of the five different household head 10-year age range samples. The CPS data is used to obtain measures of occupation-specific unemployment rates and their responsiveness to monthly seasonality and business cycle effects.

The summary statistics for the mortgage variables are in line with the trends displayed in Figure 4.1, described earlier. We can observe that 1st and 2nd mortgage take-up is most common in the 30 to 39 year old age range and both uniformly decrease as sample age increases. In a contrasting manner, the probability of securing a home equity loan or line of credit (HELOC) increases with age up to age 50, tailing off thereafter. As indicated earlier this pattern is consistent with two priors. The first being that as individuals get older the amount of equity they own in their home increases, therefore increasing the likelihood of tapping into that stored equity via home equity withdrawal tools. The second prior is that individuals outside of working age will not make use of home equity withdrawals in order to engage in consumption smoothing resulting from shocks to employment; thus older individuals are less likely to hold HELOCs.

The next set of summary statistics presented in Table 4.1 pertains to the key control variables in explaining the probability of securing a HELOC. These include three variables related to unemployment risk and variability: the 1993 to 2002 average occupation- and age group-specific unemployment rate; the seasonality in occupation-specific unemployment rate; and the business cycle effect on occupation-specific unemployment rate. All these measures are calculated using monthly CPS data. As expected, Table 4.1 shows average unemployment rates are highest for the youngest age cohort decreasing steadily as age increases and increasing slightly for the oldest age group.

In order to obtain the measures of seasonality and business cycle effects on occupation-specific unemployment rate, for each occupation a linear probability model of whether someone is unemployed is run using the following explanatory variables: monthly fixed effects; quarter-on-quarter percentage change in Gross Domestic Product (GDP); education level (less than HS, HS degree, or some college and higher levels); age; age squared; and gender. The seasonality measure is obtained by calculating the difference between the largest and smallest monthly fixed effect estimate. Business cycle effect on occupation-specific unemployment rate is the absolute value of the estimated coefficient on quarterly percent change in GDP. The absolute value is used since both a positive or negative correlation with GDP changes imply business cycle driven variability in occupation-specific unemployment rate. Both these measures are evenly distributed across age-group samples, although younger household heads tend to be employed in occupations that are slightly more responsive to business cycle effects.

The remaining key control variable for assessing the probability of someone securing a HELOC is the estimated maximum increase in the Federal Housing Finance Agency's (FHFA) metropolitan area all transactions house price index.[33] This is obtained by matching the metropolitan areas in the FHFA dataset with those identified for individuals in the ACS and making use of the variable in the ACS that identifies how long ago people moved into their home. With these two variables one can estimate the maximum house price index (HPI) appreciation since someone moved in.[34]

One concern with this measure pertains to the variable indicating how many years have elapsed since someone moved into their home being coded in intervals that become wider as the number of years increases. Concretely, if someone moved in to their home 15 years ago, they will be coded as having moved in between 11 and 20 years ago; conversely someone who moved in within the last year is accurately coded as having moved in within the last year. In calculating the maximum HPI increase for the person who moved in 15 years ago, I track the changes in the HPI since 20 years before they are surveyed and identify what the maximum increase is in the index. This could mean that the person in the example would never have experienced the

[33] Available at http://www.fhfa.gov/DataTools/Downloads/Pages/House-Price-Index.aspx .

[34] When matching cannot be done based on the metropolitan area, the state level HPI is matched instead.

calculated maximum HPI increase if this occurred between 16 and 20 years ago, since they hadn't moved into their home yet. Therefore this measure will be noisiest for older individuals, who have typically lived in their homes for longer periods. Given the way this measure is calculated it is unsurprising Table 4.1 shows the mean value of house price index appreciation increases with age.

One expects this house price appreciation estimate to strongly influence the probability of securing a HELOC. The larger the house price appreciation, the higher the house equity growth a homeowner likely experiences. This therefore increases the ability to tap into that equity via a HELOC. Conversely, homeowners who have not experienced such house price appreciation are less likely to have positive net equity in the home and therefore are unable to tap into it.

Other household head variables included in the analysis are socio-demographic attributes with a similar distribution across age groups. The obvious exceptions being: age; number of children; years since moved into their homes; marriage rates; and yearly pre-tax income.

The remaining variables are household attributes pertaining to family formation. The variables indicating number of children under 18 and number within college age (18 to 22 years old) serve may indicate that someone will make use of home equity withdrawals to deal with expenses associated with having children within these age ranges. Unsurprisingly no 20 to 29 year olds have a child of college age and only about 4% of 30 to 39 year olds have one. The married couple indicator is likely to be positively correlated with the ability to secure a loan since couples will typically have greater earnings than single people.

4.3 Conceptual Model and Identification Strategy

4.3.1 Conceptual Model

The conceptual model presented in this paper analyzes households' decision to carry out a home equity withdrawal when facing a stochastic future-period income. Although this decision can be thought of in a lifecycle utility maximization framework, the decision can be simplified into a series of decisions in a two-period model. This paper's model has a similar setup to that of Shore and Sinai (2010) and assumes that individuals maximize a two-period utility function with only one argument: consumption (c). Individuals earn a certain first-period income (y_1) and a stochastic second-period income ($\tilde{y}_2$). In the first period, individuals choose their level of consumption (c_1) and whether to secure a home equity line of credit (H). In the second period they choose whether to: draw upon the HELOC, if they had set one up; carry out a cash-out mortgage refinancing (R); or do neither. Note that the model assumes individuals currently hold a primary mortgage. This is done in order to match up with the data in this analysis which only identifies whether households hold a HELOC if they also hold a primary mortgage. However, the model can be generalized to thinking of the cash-out mortgage refinancing decision as a decision of whether or not to sell one's home.

Securing a HELOC will incur a first period fixed cost k_H and a variable cost in the second period equal to the interest rate r_H multiplied by the amount withdrawn. This is consistent with the fact that once set up and thus having incurred the fixed cost, HELOCs can be drawn upon as needed to face consumption shocks, only incurring the interest rate associated with that withdrawal amount. Since credit issuers are unlikely to give individuals with low or no income the option of securing a HELOC, the model assumes that the decision to secure a HELOC is carried out in the first period, where income is certain. Since income in the second period is stochastic, a strong negative realization may prevent individuals from having access to a HELOC thus the decision is made in the first period.

Carrying out a cash-out mortgage refinancing will incur fixed cost k_R. Unlike the decision to secure a HELOC, the model assumes the refinancing decision is made in the second period once the realization of income ($\tilde{y}_2$) is known. This assumption is due to the fact that when cash-out mortgage refinancing occurs, the amount of cash or equity extracted is decided at that time; conversely, a HELOC can be drawn upon as needed. The difference in the cost associated with these two alternate methods of carrying out home equity withdrawals arises both through differences in the fixed cost and variable cost. Securing a HELOC has a lower fixed cost ($k_H < k_R$) but incurs a variable cost ($r_H > 0$) dependent on the amount drawn; whereas the cash-out refinance option only incurs the fixed cost.

The two-period utility function that is maximized is:

$$U(c_1, c_2) = U(c_1) + U(c_2)$$

The maximization is subject to the following inter-temporal budget constraints, depending on whether or not individuals choose to carry out home equity withdrawals, and whether they do so by securing a HELOC or carrying out a cash-out mortgage refinancing:

Constraint with no home equity withdrawal: $y_1 + \tilde{y}_2 = c_1 + c_2$

Constraint with HELOC secured: $y_1 + \tilde{y}_2 + (y_1 - \tilde{y}_2) = c_1 + c_2 + k_H + r_H(y_1 - \tilde{y}_2)$

Constraint with cash-out refinancing: $y_1 + \tilde{y}_2 + (y_1 - \tilde{y}_2) = c_1 + c_2 + k_R$

For simplicity, the budget constraints with home equity extraction assume that in the second period individuals will extract home equity in such a way that they make second-period income equal to first-period income, therefore extracting an amount equal to $y_1 - \tilde{y}_2$. Obviously, if the realized value of stochastic second-period income ($\tilde{y}_2$) is greater than or equal to first-period income (y_1) no equity is withdrawn. The rationale behind this is that they will use home equity withdrawals in order to suffer no income losses from one period to the next. Whenever a home equity withdrawal is carried out, a further constraint is imposed. The constraint is that you can only extract equity up to the value of home equity that you own, *i.e.* home equity $\geq y_1 - \tilde{y}_2$. Individuals who experience appreciation in house prices are likely to see an increase in their level of home equity. This therefore increases their likelihood of being able to extract some of that home equity by either carrying out a cash-out refinancing or securing a HELOC. This situation probably impacts young homeowners the most since they are likely to be credit-constrained at the time of home purchase. Therefore appreciation in house prices will likely mean they get into a positive net home equity position, giving them the possibility of carrying out a home equity withdrawal.

Given this setup, second period consumption (c_2) is either:

c_2 with no home equity withdrawal: $c_2 = y_1 + \tilde{y}_2 - c_1$

c_2 with HELOC secured: $c_2 = y_1 + \tilde{y}_2 - c_1 - k_H + (1 - r_H)(y_1 - \tilde{y}_2)$

$$c_2 = 2y_1 - c_1 - k_H - r_H(y_1 - \tilde{y}_2)$$

c_2 with cash-out refinancing: $c_2 = y_1 + \tilde{y}_2 - c_1 - k_R + (y_1 - \tilde{y}_2)$

$$c_2 = 2y_1 - c_1 - k_R$$

Knowing second-period levels associated with each option enables one to write down the inter-temporal utility maximization problem that individuals face, shown below:

$$\max_{c_1,H,R} \left\{ \begin{array}{c} U(c_1) + (1 - H) * (1 - R) * \mathrm{E}[U(y_1 + \tilde{y}_2 - c_1)] \\ + H * \mathrm{E}\big[U\big(2y_1 - c_1 - k_H - r_H(y_1 - \tilde{y}_2)\big)\big] + R * U(2y_1 - c_1 - k_R) \end{array} \right\}$$

Where $\mathrm{E}[U(\ldots)]$ is the expectation of second-period utility, *H* is an indicator of securing a HELOC, and *R* indicates a cash-out mortgage refinancing is carried out. While this paper does not attempt to fully solve the maximization problem shown above, it will assess how different realizations of second-period income ($\tilde{y}_2$) impact optimal choices.

Figure 4.2 displays how the second-period shock to consumption $(y_1 - \tilde{y}_2)$ varies with different realizations of second-period income ($\tilde{y}_2$) and the choices of whether to secure a HELOC or perform a cash-out mortgage refinancing. From the figure we can observe that for any realized value of second-period income ($\tilde{y}_2$) smaller than $y_1 + (k_H - k_R)/r_H$, performing a cash-out mortgage refinancing is optimal since it minimizes the shock to second-period consumption. A realization such that $y_1 + (k_H - k_R)/r_H \leq \tilde{y}_2 \leq y_1 - k_H/(1 - r_H)$, makes taking out a HELOC in the first-period and drawing upon it in the second-period optimal. While any realization larger than $y_1 - k_H/(1 - r_H)$ implies no home equity withdrawal is optimal.

This framework identifies how small shocks to consumption such as the ones resulting from temporary breaks to employment can make it optimal for households to secure access to a home equity line of credit in order to smooth consumption during these periods. Note that the model doesn't explicitly account for the fact that once a HELOC has been secured, it can be used for an extended period of time. This likely makes securing a HELOC an even more attractive proposition for households who experience frequent and predictable shocks to consumption through temporary spells of unemployment. Such spells may be driven by occupation-specific employment's seasonality or reactiveness to business cycle effects. These ideas drive the identification strategy presented in the next section.

4.3.2 Identification Strategy

Having presented the conceptual model that underpins the analysis to be carried out, this section details the empirical identification strategy. The first thing to note is that estimating equations are run separately for five different samples of household head ten-year age ranges.

This is done because there are important differences in the housing equity, mortgage holdings, and home equity withdrawal behavior across age groups that this analysis will highlight.

For all the equations presented in this section, the variable $HELOC_{i,s,t}$ identifies whether household *i* in metropolitan area *m* and state *s* in year *t* has secured a home equity loan or line of credit. Ideally one would look at both the intensive (amount of equity withdrawn) and extensive (securing a HELOC) margin. However, due to data limitations only the latter is possible. Ordinary least squares linear probability models are estimated throughout the paper.[35] The baseline model has the following estimating equation:

$$HELOC_{i,m,s,t} = \alpha + \beta_1 Max.\%\ HPI\ Increase_{i,m,t} + \beta_2 Avg.U.Rate_i + \beta_3 UR\ Seasonality_i$$
$$+\beta_4 UR\ Bus.Cycle\ Effect_i + \partial X_{i,t} + \gamma_i + \lambda_{s,t} + \varepsilon_{i,t} \quad (1)$$

As previously indicated, the variable $Max.\%\ HPI\ Increase_{m,t}$ is likely to have a significant impact on the probability of households securing a HELOC. An increase in housing prices will be correlated with net home equity increases. For example, say a takes out a \$200,000 mortgage to buy a \$300,000 home and housing prices increase in such a way that the home is worth \$330,000 in a year. This means that this household now has a \$30,000 increase in home equity which they can tap into using a HELOC. Having experienced an increase in home equity is also makes it more likely that credit issuers will be willing allow these households to secure a HELOC. Therefore the overall effect of house price appreciation on the probability of securing a HELOC is expected to be positive.

The variables $Avg.U.Rate_i$, $UR\ Seasonality_i$, and $UR\ Bus.Cycle\ Effect_i$ are measures of unemployment risk and variance. These measures are calculated using CPS 1993-2002 data using the methods described in the Data section of this paper. All three of these

[35] The baseline model (eqn. 1) is also estimated using Probit regressions. Estimated marginal effects are comparable to the ones obtained from the linear probability model and are available upon request.

variables are expected to positively influence demand for home equity withdrawals if consumption smoothing motives exist. However, as pointed out by Duca and Kumar (2014), when assessing the equilibrium level of home equity withdrawal one needs to also factor in how these same attributes affect the supply of home equity withdrawal options. All three of these measures are likely to have a negative effect on the supply of HELOCs since they indicate to credit suppliers that these people are riskier borrowers. The overall effect on the equilibrium probability of holding a HELOC may therefore be negative. When from a strictly consumption smoothing perspective we expect the opposite.

All three of the variables pertaining to unemployment risk and variance may also be negative due to the influence of unobserved wealth. Wealth is positively correlated with people's ability to secure a HELOC and is likely to be negatively correlated with some of these occupation-specific measures of unemployment risk and variance. This may again lead to negative estimated coefficients for these variables independently of consumption smoothing motives. On the other hand, finding positive coefficients indicates consumption smoothing motives are probably behind the decision to secure a HELOC.

The vector $X_{i,t}$ contains the household head attributes described in Section II and detailed in Table 4.1. The remaining variables are a series of fixed effects that aid in identification. $\gamma_i$are household head occupation group fixed effects. In total there are 336 occupations in the 1990 Census Bureau occupational classification scheme. For most of the empirical specifications occupations are broken into 17 broader groups and fixed effects for these broad groups are included (see Table A4-1 for details). However models are also run where the full 336 occupation fixed effects are included. As previously mentioned occupational standing is likely to be correlated with unobserved wealth so including these fixed effects will aid in diminishing the bias occurring through this channel. In all estimating equations state by year fixed effects ($\lambda_{s,t}$) are also included. Given that in the period of time of the analysis there are significant differences in credit issuing standards across years and states, omission of these fixed effects would likely bias results.

Having highlighted the important role house price appreciation may have on the ability to secure a HELOC, the model detailed in equation (2) interacts estimated house price increase with the various unemployment risk and variance measures. Figure 4.3 displays how the market for HELOCs is impacted by house price appreciation which aid in explaining the rationale behind the inclusion of such interaction terms in the model.

$$\begin{aligned} HELOC_{i,m,s,t} &= \alpha + \beta_1 Max.\%\,HPI\ Increase_{i,m,t} + \beta_2 Avg.U.Rate_i + \beta_3 UR\ Seasonality_i \\ &+ \beta_4 UR\ Bus.Cycle\ Effect_i + \beta_5 HPI\ Increase * Avg.U.Rate_{i,m,t} \\ &+ \beta_6 HPI\ Increase * UR\ Seasonality_{i,m,t} \\ &+ \beta_7 HPI\ Increase * UR\ Bus.Cycle\ Effect_{i,m,t} + \partial X_{i,t} + \gamma_i + \lambda_{s,t} + \varepsilon_{i,t} \qquad (2) \end{aligned}$$

Figure 4.3 presents two separate demand functions; one for low unemployment risk occupations and one for high. Higher unemployment risk in this case can be expressed in higher seasonality; business cycle driven fluctuations; or higher overall unemployment rate. Low unemployment risk occupations will have a smaller demand for HELOCs for consumptions smoothing motives than high risk occupations. The demand for low risk occupations is therefore less elastic; highlighting how changes in the interest rate charges on HELOCs will have little influence on quantity demanded. Conversely, high risk occupations will be more responsive to changes in interest rate in their demand for HELOCs since they have a higher latent demand for such home equity withdrawal devices driven by consumption smoothing motives.

Assuming that the increase in home equity driven by house price appreciation predominantly increases the supply of HELOCs, Figure 4.3 displays how this shift in supply enables one to trace out the demand for HELOCs of low and high unemployment risk occupations. The figure shows how the expected increase in the equilibrium level of HELOC holdings in response to a supply shift is larger for high risk occupations than low risk ones. Therefore the coefficients on the interaction terms are expected to be positive. Especially so for younger households who absent the house price appreciation are unlikely to be offered the option of securing a HELOC.

In all estimating equations, reported standard errors are clustered at the state level in order to account for within state correlation across observations. The models presented in equations (1) and (2) are also run separately household heads with low or high occupation- and age-specific unemployment rates. The cutoff used for this split is an unemployment rate of 5%. This is done in order to assess how individuals with differing baseline levels of unemployment differentially react to unemployment risk and variance measures in their decision to secure a HELOC.

Authors have cautioned that the use of occupation-specific unemployment risk and variance measures may be unadvisable due to the correlation between occupation choice and people's risk aversion (Lusardi, 1997) or access to credit (Berhardt and Backus, 1990). As a robustness check in order to address this issue, the models in equations (1) and (2) are also run separately for two-worker households with differing degrees of spousal correlation in unemployment rate. Higher spousal correlation in unemployment rates diminishes the likelihood that individuals will be able to use spouse's income to compensate for breaks in consumption resulting from unemployment spells. This builds on the identification strategy used by Shore and Sinai (2010) who used the fact that same occupation couples will face a higher correlation in unemployment shocks than different occupation couples to assess their differential consumption of housing.

Spousal correlation in unemployment rate is obtained by estimating occupation-specific unemployment rates for the years 1993 to 2002 using CPS data and calculating the correlation coefficient in the unemployment rates for different occupation pairs. Having obtained these correlation coefficients, two-worker households are split into three groups: those with negative or zero correlation (coefficient between -1 and 0); those with weak positive correlation (coefficient between 0 and 0.5); and those with strong positive correlation (coefficient between 0.5 and 1). These cutoffs are chosen to reflect differing likelihoods of being able to use spousal income to substitute for own income during unemployment spells. In all the models for two-worker households both household head and spouse attributes and broad occupation group fixed effects are included in the regressions in order to capture differential probabilities of holding a HELOC driven by differences in the characteristics of the second worker in the household.

4.4 Results

4.4.1 Baseline Model

Table 4.2 presents the results for the baseline model. This is the only table that reports the coefficients associated with the full set of explanatory variables. The remaining tables only report coefficients on the key explanatory variables since the remaining ones do not change significantly across specifications.

The coefficient for maximum percentage house price index (HPI) increase since moved in is seen to be consistently positive across age groups. The magnitude of the coefficient also decreases slightly with age. This reflects the fact that older individuals are likely to have more equity even without an appreciation in their house's valuation. It may also reflect how this measure is likely to suffer from attenuation bias for individuals who have been in their house longer, typically older individuals, due to the greater margin for error in estimating house price appreciation for people who've lived in their homes longer. The positive coefficient being larger for younger households is also consistent with these households being most likely to be credit constrained and therefore requiring an increase in home equity to be able to secure a HELOC.

The variable indicating the age- and occupation-specific unemployment rate shows a consistently negative impact on the probability of securing a HELOC. As previously mentioned, occupational unemployment rate is likely to be correlated with unobserved wealth. The negative coefficient is therefore unsurprising since the negative unobserved wealth effect is likely to dominate any positive effects occurring through consumption smoothing desires. Similarly, the coefficient on the measure of seasonality in unemployment rate is also likely to suffer from unobserved wealth bias. Accordingly, significantly negative coefficients on this variable are evident for the two oldest age cohorts. For these groups the average unemployment rate no longer has such a strong negative effect and instead unemployment seasonality may be picking up the unobserved wealth effect. For younger age cohorts the positive impact on the coefficient driven by consumption smoothing motives outweighs any negative unobserved wealth effects, but the coefficient is only significant positive coefficient for household heads aged 30 to 39.

The strongest evidence of consumption smoothing motives potentially driving the probability of households securing a HELOC in this baseline model is seen in the coefficients for the business cycle effect on occupation-specific unemployment rate. The coefficient is positive for all age groups and significantly so for all but the oldest cohort. For individuals under age 40 the coefficient has the largest magnitude implying an effect of approximately a 0.2 percentage point increase in the probability of securing a HELOC, when evaluated at the mean. Although this is a small effect, given the low baseline probabilities of holding a HELOC the estimated impacts represent a 2.7 and 1.3 % increase, for those aged 20 to 29 and 30 to 39, respectively.

It is important at this point to remind ourselves of a key limitation in the data: the fact that we do not observe whether or not an individual holds a HEL or HELOC unless they also hold a primary mortgage. This restriction is unlikely to be very taxing on the credibility of estimates for people between the ages of 22 and 52 since these groups have primary mortgage holding rates above 80%. However, for very young and older cohorts there may be something different about households who hold a mortgage relative to the general population. This leads to a selection bias that can impact the credibility of estimated coefficients. Therefore estimates for the samples of household heads aged 30 to 50 are probably cleanest from this selection bias. Conversely, estimates for the oldest age cohort are most likely to be biased for this reason.

The remaining coefficients generally have the expected influence on the probability of securing a HELOC. Being a household where the household head is female consistently decreases the probability of securing a HELOC. This occurs even after controlling for the positive impacts of being married and of total household yearly pre-tax income on that same probability. The coefficients on age an age squared match up with the trends in the probability of holding a HELOC shown in Figure 4.1.

Education variables' coefficients show higher levels of education are positively correlated with securing a HELOC. This is consistent with the fact that education is a proxy for unobserved wealth; therefore higher education likely means higher wealth thus greater access to credit. These findings are also consistent with the work of Duca and Kumar (2014) who show that financially literate individuals are less likely to withdraw equity from their homes via non-home equity loans.

The breakdown of coefficients by race shows evidence of racial attributes likely being correlated with wealth thus affecting the credit access of different individuals. The non-white and Hispanic coefficients are both consistently negative and significant across age groups. Similarly US citizenship has a consistently positive correlation with securing a HELOC. This likely reflects both the higher earnings and wealth of these individuals relative to non-citizens, but also the fact that non-citizens are likely to have a smaller credit history, leading to lower credit rating and lower likelihood of securing a HELOC.

Years since someone moved in is shown to have a non-linear relationship with the probability of securing a HELOC; years since moved in has a positive coefficient and the square of this variable has a negative coefficient. Years since moved in are a proxy for mobility. The longer someone has been in a home, the more likely they will remain in that home. A positive relationship is therefore expected since people who are more likely to move elsewhere are less likely to take out credit using their home as collateral. This measure is also likely to be correlated with owning a greater share of equity in the home, therefore increasing the ability to draw upon it by securing a HELOC. House age is also included as a control to account for the fact that homeowners may want to secure a HELOC in order to carry out maintenance. Since an older home is expected to require more maintenance, one would expect the coefficient to be positive. The significantly negative coefficient may however once again reveal unobserved wealth effects because wealthier individuals are more likely to own newer homes.

The variables indicating the number of college age children (18 to 22 years old) and number of children under age 18 generally show a positive correlation with securing a HELOC.

This is consistent with the fact that households may wish to take out credit to deal with expenses associated with having children within these age ranges. The exception to this occurs for younger age groups. One explanation for the negative coefficient observed for people within the 30 to 39 age range having a child of college age, is that these are outliers in the data. It is not common for someone within this age group to have a child of this age and when they do, it probably reflects the fact that these individuals have a smaller attachment to the labor force thus decreased earnings leading to lower ability to obtain credit.

Overall the results from this baseline model begin to shed light on how unemployment risk and variance can drive demand for securing a HELOC, consistent with consumption smoothing motives. In the next section results from the model which interacts house price appreciation with the various measures of unemployment risk and variance will provide clearer evidence of how frequent and predictable shocks to employment can drive the decision to secure a HELOC; particularly so for younger age groups.

4.4.2 Interacted Model

Table 4.3 presents the results obtained using the model specification which interacts the estimated maximum house price appreciation with the various unemployment risk and variance measures using the specification detailed in equation (2). The interaction of house price increase and the occupation- and age-specific average unemployment rate reveals that the positive effect of house price appreciation on the probability of securing a HELOC is diminished if household heads belong to high average unemployment rate occupations. This mirrors the effect of average unemployment rate found in the model with no interactions which was significantly negative for all but the oldest cohort. As mentioned earlier, this average unemployment rate is probably captured an unobserved wealth effect. Therefore when facing a similar increase in house prices, individuals in high unemployment rate occupations are still less likely to be able to secure a HELOC than those in lower unemployment rate occupations.

The effects of seasonality and business cycle induced fluctuations in occupational unemployment rate on the probability of securing a HELOC are seen to be larger when younger individuals experience growth in house prices since the interaction terms are positive. Young individuals are most likely to be credit-constrained when they move into their homes, *i.e.* they are likely to have "maxed out" the amount of credit they can obtain in order to finance their home purchase through taking out a mortgage. Therefore for younger households increases in house prices will have a greater impact on their ability to secure a HELOC than older individuals. Given this, the evidence in Table 4.3 shows that it is workers in occupations with greater variance in unemployment rate that are most likely to take advantage of house price appreciation and corresponding increases in home equity in order to secure a HELOC.

Table 4.4 shows the results of carrying out the same interacted model from equation (3) as in Table 4.3 but with the inclusion of the full 338 occupation fixed effects instead of the 17 broader occupation groups. All the occupation specific measures drop out of the estimating equation because they are collinear with the occupation fixed effect. The interacted terms however remain, and we can see that the estimated coefficients on the interactions are very similar to the ones obtained in the model with only 17 broad occupation categories fixed effects. This indicates the results in Table 4.3 indeed reflect the impact of differing degrees of occupational unemployment rate seasonality and business cycle induced fluctuations on the probability of securing a HELOC instead of some other occupation-specific potentially biasing the results.

4.4.3 Comparison of household heads in low and high unemployment rate occupations

Tables 4.5 through 6B present the results from an analysis that divides household heads into those in low or high unemployment rate occupations. As detailed in Section III, this split is based on a 5% unemployment rate cutoff. Breaking the sample up in such a manner reveals important differences in the degree to which frequent and predictable breaks to employment impact the decisions of securing a HELOC across groups.

Table 4.5 reveals that workers in lower unemployment rate occupations, or in occupations with lower risk of unemployment, still exhibit an increased likelihood of securing a HELOC when facing business cycle induced fluctuations in unemployment rate. This is consistent with the idea of HELOCs providing a mechanism through which households can tap into stored home equity to smooth out shocks to consumption. On the other hand, seasonality in employment is seen to have a negative influence on the probability of securing a HELOC. This may reflect the fact that for these workers any consumption smoothing motives for securing a HELOC are not strong enough to outweigh negative unobserved wealth effects. The results may also indicate that for low unemployment rate occupations seasonality in employment is less of a factor since the probability of becoming unemployed is small anyway.

By contrast to those in the lower unemployment risk sample, household heads in high unemployment rate occupations are seen to react more to seasonality in employment than to business cycle effects in their decision to secure a HELOC. Interestingly, whereas in the whole sample analysis only those under age 40 exhibited an increased tendency to secure a HELOC when facing seasonality in employment, all samples under age 50 in this split of the data display such a tendency. Interacted model results in Table 4.6B further reveal that for the youngest age cohort house price appreciation is still needed in order for workers with high unemployment seasonality to be able to secure a HELOC.

4.4.4 Comparison of two-worker households by degree of spousal unemployment rate correlation

Table 4.7 shows that splitting up the two-worker household sample by the degree of spousal occupation-specific unemployment rate correlation reveals important differences in the extent to which such households react to employment variability.[36] Recall that individuals in two-worker household with higher correlation in spousal unemployment rates are less able to use spousal income in order to insure against shocks to their own income. Therefore one expects such households are more likely to protect against frequent and predictable shocks to employment by securing access to a HELOC. Results expose that indeed this is the case.

The impact of seasonality in employment on the probability of securing a HELOC is positive and significant for household heads under age 40 with a strong positive correlation in spousal unemployment. No such significant effects of seasonality are seen for other samples. Similarly, the impact of business cycle driven fluctuations to employment on the probability of securing a HELOC is also strongest for two-worker households with a strongly positive spousal unemployment rate correlation.

The interacted model results for households with a strong spousal unemployment rate correlation are presented in Table 4.8. These confirm that for younger people the impacts of both seasonality and business cycle driven fluctuations to employment on the probability of securing a HELOC are stronger when paired with house price appreciation.

[36] Results for the whole sample of two-worker households are similar to those for all households presented in Tables 3 and 4 therefore are not included in the paper tables but are available upon request.

Results from this model specification are particularly appealing because identification of differential effects occurs through the influence of a variable that is less likely to be correlated with individuals risk aversion. As mentioned earlier, people's occupation choice is likely to be correlated with their degree of risk aversion. Therefore more risk averse people will likely select into occupations with less unemployment risk. On the other hand, it is unlikely individuals choose their spouses on the basis of their aversion to unemployment risk.

4.5 Conclusion

This paper finds evidence that facing frequent and predictable spells of unemployment can induce households to increase their demand for home equity loans or lines of credit (HELOC). Household heads under age 60 with occupational unemployment rates that are significantly impacted by business cycle effects are more likely to secure a HELOC. Results also indicate household heads under age 40 facing occupational seasonality in unemployment tend to secure such home equity withdrawal devices. For this younger group evidence is strongest when also experiencing an increase in their level of home equity via house price appreciation. This enables them to overcome credit supply restrictions and gain access to these home equity withdrawal devices.

Addressing concerns pertaining to the correlation between occupational choice and individual's risk aversion, a robustness check is carried out which compares outcomes for two-worker households by the degree of spousal correlation in unemployment rates. Results indicate households with a strong positive correlation in unemployment rates are more likely to secure access to HELOCs when facing seasonality and business cycle induced fluctuations in employment. This reflects their lesser ability to use spousal income as an alternative method for smoothing consumption relative to lower spousal unemployment correlation couples

The findings here confirm the importance of home equity as a buffer stock of income that can be used to smooth out temporary shocks to consumption, consistent with the literature (*e.g.* Benjamin and Chinloy, 2008; Carroll, Dynan and Krane, 2003; Davidoff, 2006; Schwartz *et al*, 2008; Shore and Sinai, 2010; and Wood *et al*, 2013). This paper highlights the previously unexplored and important role that home equity lines of credit may play in this context.

Future research would benefit from identifying to what extent households draw upon home equity lines of credit when facing shocks to employment; i.e. analyzing what the dollar amount of equity extraction is. This is something that cannot be done with the ACS data used in this analysis but would provide important information regarding the extent to which such HELOC drawings can be used for consumption smoothing purposes in the context of unemployment spells. Another fruitful avenue for future research would be to analyze how such unemployment risk factors identified in this paper contribute to the decision of carrying out home equity withdrawals for households without a primary mortgage.

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Figure 4.1
Probability of holding a 1st mortgage for all households and probabilities of also holding a 2nd mortgage and home equity loan (HEL) or line of credit (HELOC) for those holding a 1st mortgage (2003-2013)

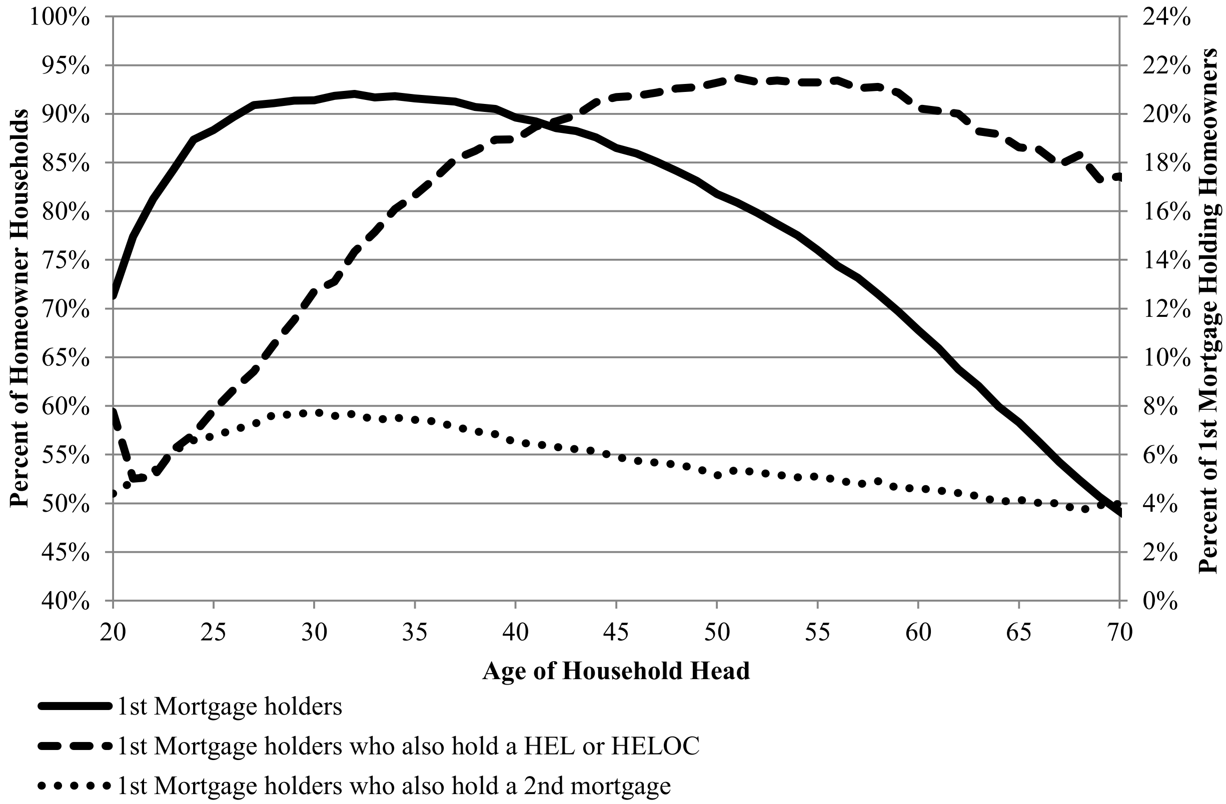

Figure 4.2
Conceptual Model: Second-period consumption shock as a function of the decision to execute a home equity withdrawal

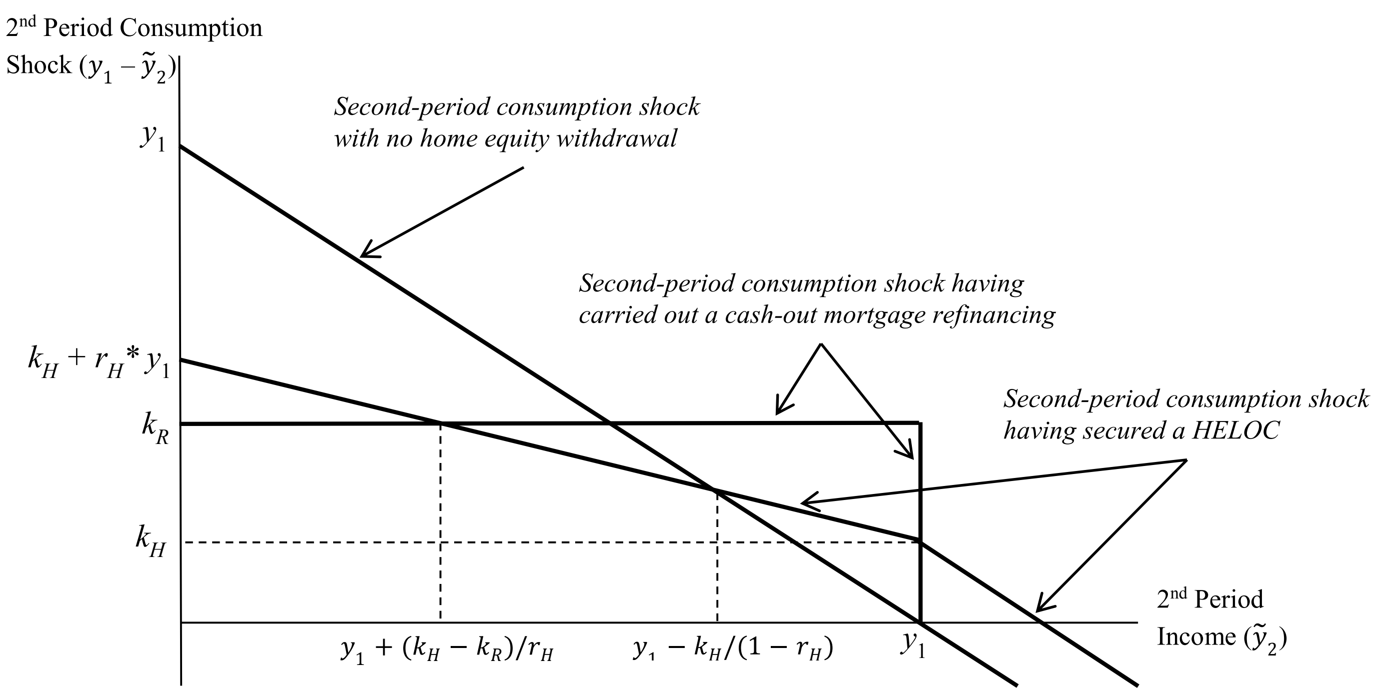

Figure 4.3
Equilibrium outcomes in the home equity line of credit (HELOC) market when experiencing house price appreciation for low and high unemployment risk occupations

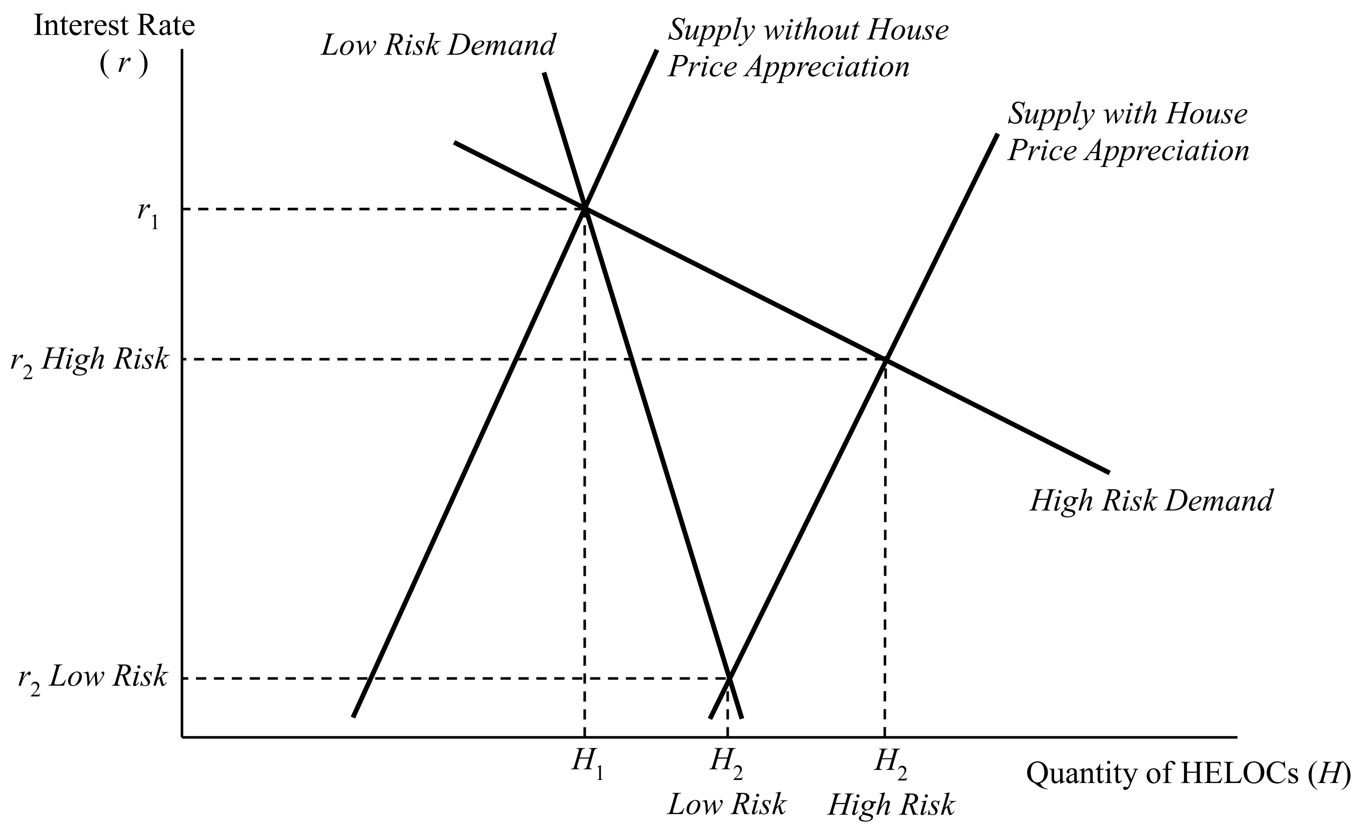

Table 4.1
Summary statistics
(Standard deviation shown in parentheses)

	Age group year range (by Household Head Age)									
	20-29		30-39		40-49		50-59		60-69	
	Mean	(S.D.)	Mean	(S.D.)	Mean	(S.D.)	Mean	(S.D.)	Mean	(S.D.)
Mortgage Variables										
% Hold a Home Equity Loan or Line of Credit [a]	8.4	(27.7)	15.2	(35.9)	17.8	(38.3)	16.5	(37.1)	11.8	(32.3)
% Hold a Mortgage	89.1	(31.1)	91.4	(28.1)	86.7	(34.0)	76.6	(42.3)	60.8	(48.8)
% Hold a Second Mortgage [a]	6.4	(24.5)	6.8	(25.2)	5.3	(22.3)	3.9	(19.4)	2.6	(16.0)
Key Control Variables										
Estimated Max. % HPI Increase Since Moved In	0.207	(0.276)	0.365	(0.338)	0.602	(0.432)	0.814	(0.528)	0.936	(0.568)
Avg. UR for Age and Occ. Group 1993-2002	0.051	(0.036)	0.036	(0.028)	0.032	(0.022)	0.031	(0.021)	0.034	(0.022)
Seasonality in Occupation-Specific UR [b]	0.023	(0.027)	0.021	(0.025)	0.021	(0.026)	0.021	(0.026)	0.022	(0.026)
Business Cycle Effect on Occ.-Specific UR [b]	0.400	(0.396)	0.407	(0.392)	0.402	(0.389)	0.388	(0.385)	0.369	(0.375)
Remaining Household Head Variables										
Female	0.46	(0.50)	0.42	(0.49)	0.39	(0.49)	0.39	(0.49)	0.37	(0.48)
Married	0.55	(0.50)	0.69	(0.46)	0.68	(0.47)	0.65	(0.48)	0.64	(0.48)
Education- Less than High School	0.05	(0.22)	0.05	(0.22)	0.06	(0.24)	0.06	(0.24)	0.08	(0.27)
Education- High School Graduate	0.21	(0.40)	0.19	(0.39)	0.23	(0.42)	0.24	(0.42)	0.25	(0.43)
Education- Some College or Higher	0.74	(0.44)	0.76	(0.43)	0.71	(0.45)	0.71	(0.46)	0.68	(0.47)
Age	26.4	(2.2)	34.9	(2.8)	44.7	(2.9)	54.3	(2.9)	63.6	(2.7)
Non-White	0.16	(0.37)	0.20	(0.40)	0.18	(0.39)	0.16	(0.36)	0.13	(0.34)
Hispanic	0.12	(0.32)	0.12	(0.33)	0.10	(0.30)	0.07	(0.25)	0.05	(0.22)
US Citizen	0.95	(0.21)	0.93	(0.25)	0.95	(0.21)	0.97	(0.16)	0.98	(0.13)
Veteran	0.01	(0.12)	0.02	(0.13)	0.03	(0.17)	0.04	(0.21)	0.10	(0.30)
Household Yearly Pre-Tax Income (1,000 $)	50.1	(36.8)	74.2	(61.4)	81.2	(72.3)	79.7	(74.1)	69.8	(70.9)
Number of Children Under Age 18	0.00	0.00	0.04	(0.20)	0.22	(0.49)	0.18	(0.45)	0.04	(0.20)
Number of College Age Children (aged 18-22)	0.72	(0.99)	1.40	(1.22)	1.08	(1.14)	0.27	(0.65)	0.03	(0.24)
Years Since Moved In	4.4	(4.7)	7.4	(6.0)	12.3	(8.0)	16.9	(9.6)	19.6	(10.2)
House Age (current year – year built)	32.0	(23.0)	31.0	(22.8)	32.6	(21.8)	35.2	(21.0)	36.9	(20.5)
Observations	311,226		980,508		1,505,778		1,666,668		1,037,849	

[a] Second mortgage and home equity loan or line of credit status only observed for individuals that hold a primary mortgage.
[b] Measures are calculated by regressing unemployment status on month fixed effects, quarterly percent change in GDP, education, age, age squared, and gender using CPS 1993-2002 data for each occupation. Seasonality is the difference between the largest and smallest monthly fixed effect estimate. Business cycle effect is the absolute value of the coefficient estimate for quarterly percent change in GDP.

Table 4.2
Linear probability model of securing a HEL/HELOC for all households (2003-2013)[a]
(standard errors clustered at state level in parenthesis)

Dependent variable = 100 if hold a HEL or HELOC; 0 otherwise.

	Age group year range (by Household Head Age)				
	20-29	30-39	40-49	50-59	60-69
Estimated Max. % HPI Increase Since Moved In (HPI)	8.500***	8.209***	5.688***	3.904***	2.985***
	(1.601)	(1.684)	(1.481)	(1.172)	(1.073)
Avg. UR for Age and Occ. Group 1993-2002 (UR)	-9.213***	-28.62***	-25.55***	-9.247***	-2.166
	(2.143)	(3.121)	(2.837)	(2.256)	(2.067)
Seasonality in Occupation-Specific UR (S): [b]	1.979	7.730***	-0.612	-7.637***	-8.053***
High – Low Monthly Factor	(2.510)	(2.565)	(1.481)	(1.402)	(1.659)
Business Cycle Effect on Occ.-Specific UR (BC): [b]	0.567***	0.474***	0.217**	0.273**	0.0412
Impact of Quarterly % Change in GDP	(0.178)	(0.137)	(0.0867)	(0.105)	(0.102)
Household Head Attributes					
Female	-0.387***	-0.915***	-1.013***	-0.810***	-0.949***
	(0.102)	(0.137)	(0.144)	(0.115)	(0.114)
Married	1.449***	3.401***	3.879***	3.428***	1.678***
	(0.173)	(0.314)	(0.315)	(0.301)	(0.197)
Education- High-School Degree	1.127***	1.673***	2.283***	2.323***	1.193***
	(0.341)	(0.503)	(0.455)	(0.514)	(0.273)
Education- Some College or Higher	1.963***	4.474***	5.094***	4.830***	3.775***
	(0.400)	(0.662)	(0.546)	(0.608)	(0.373)
Age	-2.155***	1.435***	0.922**	1.684***	-1.308**
	(0.448)	(0.324)	(0.346)	(0.373)	(0.639)
Age Squared	0.0501***	-0.0158***	-0.00992**	-0.0174***	0.00679
	(0.00892)	(0.00467)	(0.00388)	(0.00336)	(0.00499)
Non-White	-1.407***	-3.756***	-4.650***	-3.052***	-0.221
	(0.260)	(0.436)	(0.413)	(0.305)	(0.197)
Hispanic	-1.406***	-1.112**	-1.546**	-1.116*	0.0380
	(0.521)	(0.474)	(0.677)	(0.648)	(0.467)
US Citizen	0.452	1.721***	2.237***	2.207***	1.868***
	(0.310)	(0.435)	(0.347)	(0.312)	(0.491)
Veteran	-0.428	-1.854***	-1.904***	-1.056***	0.0478
	(0.370)	(0.267)	(0.249)	(0.180)	(0.0972)
Household Yearly Pre-Tax Income (1,000 $)	0.0414***	0.0330***	0.0227***	0.0174***	0.0151***
	(0.00428)	(0.00312)	(0.00231)	(0.00176)	(0.00150)
Number of Children Under Age 18	0.00876	0.366***	0.812***	0.784***	1.539***
	(0.0776)	(0.0767)	(0.0827)	(0.0628)	(0.217)
Number of College Age Children (18 to 22 yrs. old)		-1.611***	0.629***	1.696***	2.300***
		(0.211)	(0.112)	(0.157)	(0.164)
Years Since Moved In	0.925***	1.285***	1.181***	1.169***	0.982***
	(0.124)	(0.153)	(0.0917)	(0.0700)	(0.0594)
Years Since Moved In Squared	-0.0414***	-0.0544***	-0.0439***	-0.0387***	-0.0319***
	(0.00366)	(0.00400)	(0.00191)	(0.00186)	(0.00178)

(Continues on next page…)

Table 4.2 (Cont.)
Linear probability model of securing a HEL/HELOC for all households (2003-2013)[a]
(standard errors clustered at state level in parenthesis)

Dependent variable = 100 if hold a HEL or HELOC; 0 otherwise.					
	Age group year range (by Household Head Age)				
	20-29	30-39	40-49	50-59	60-69
House Age:	-0.0244***	-0.0456***	-0.0455***	-0.0435***	-0.0292***
Current Year – Year Built	(0.00322)	(0.00636)	(0.00662)	(0.00409)	(0.00313)
Constant	22.10***	-30.85***	-20.86***	-40.46***	55.12**
	(5.688)	(6.038)	(7.749)	(10.37)	(20.80)
State by Year FE	561	561	561	561	561
Household Head Broad Occupation Group FE	17	17	17	17	17
Observations	311,226	980,508	1,505,778	1,666,668	1,037,849
R-squared	0.060	0.067	0.054	0.045	0.035
Mean HEL/HELOC	8.39%	15.20%	17.83%	16.45%	11.82%
Mean Percent HPI Increase	0.207	0.365	0.602	0.814	0.936
Mean UR	0.051	0.036	0.032	0.031	0.034
Mean S	0.023	0.021	0.021	0.021	0.022
Mean BC	0.400	0.407	0.402	0.388	0.369

[a] One * indicates significant at 10% level, ** at 5%, *** at 1%.
[b] Measures are calculated by regressing unemployment status on month fixed effects, quarterly percent change in GDP, education, age, age squared, and gender using CPS 1993-2002 data for each occupation. Seasonality is the difference between the largest and smallest monthly fixed effect estimate. Business cycle effect is the absolute value of the coefficient estimate for quarterly % change in GDP.

Table 4.3
Interacting unemployment risk measures with house price index appreciation[a]
(standard errors clustered at state level in parenthesis)

Dependent variable = 100 if hold a HEL or HELOC; 0 otherwise.

	Age group year range (by Household Head Age)				
	20-29	30-39	40-49	50-59	60-69
Estimated Max. % HPI Increase Since Moved In (HPI)	10.01***	9.898***	6.449***	4.204***	3.438***
	(1.696)	(1.714)	(1.522)	(1.187)	(1.120)
Avg. UR for Age and Occ. Group 1993-2002 (UR)	0.207	-5.554	-10.42	-3.890	7.034
	(2.448)	(4.215)	(7.061)	(3.296)	(4.410)
Seasonality in Occupation-Specific UR (S): [b]	-1.186	4.275*	-2.206	-3.933	-2.128
High – Low Monthly Factor	(2.784)	(2.387)	(2.406)	(2.639)	(2.994)
Business Cycle Effect on Occ.-Specific UR (BC): [b]	0.372**	0.291*	0.303*	0.319**	0.0666
Impact of Quarterly % Change in GDP	(0.164)	(0.156)	(0.161)	(0.153)	(0.158)
Interactions					
HPI x UR	-43.14***	-59.46***	-24.03**	-6.389	-9.533**
	(5.075)	(7.868)	(9.099)	(4.661)	(3.590)
HPI x S	13.99**	9.196**	2.698	-4.210*	-6.058**
	(6.792)	(3.991)	(2.843)	(2.475)	(2.937)
HPI x BC	0.981**	0.478	-0.151	-0.0562	-0.0307
	(0.379)	(0.317)	(0.261)	(0.141)	(0.168)
State by Year FE	561	561	561	561	561
Household Head Broad Occupation Group FE	17	17	17	17	17
Observations	311,226	980,508	1,505,778	1,666,668	1,037,849
R-squared	0.061	0.067	0.054	0.045	0.035
Mean HEL/HELOC	8.39%	15.20%	17.83%	16.45%	11.82%
Mean Percent HPI Increase	0.207	0.365	0.602	0.814	0.936
Mean UR	0.051	0.036	0.032	0.031	0.034
Mean S	0.023	0.021	0.021	0.021	0.022
Mean BC	0.400	0.407	0.402	0.388	0.369

[a] One * indicates significant at 10% level, ** at 5%, *** at 1%. All models also include household head attributes.
[b] Measures are calculated by regressing unemployment status on month fixed effects, quarterly percent change in GDP, education, age, age squared, and gender using CPS 1993-2002 data for each occupation. Seasonality is the difference between the largest and smallest monthly fixed effect estimate. Business cycle effect is the absolute value of the coefficient estimate for quarterly percent change in GDP.

Table 4.4
Interacting unemployment risk measures with house price index appreciation including a full set of occupation fixed effects[a]
(standard errors clustered at state level in parenthesis)

Dependent variable = 100 if hold a HEL or HELOC; 0 otherwise.

	Age group year range (by Household Head Age)				
	20-29	30-39	40-49	50-59	60-69
Estimated Max. % HPI Increase Since Moved In (HPI)	10.03***	9.783***	6.309***	4.117***	3.372***
	(1.687)	(1.690)	(1.514)	(1.184)	(1.124)
Interactions					
HPI x UR	-43.17***	-58.75***	-23.14**	-5.964	-9.390**
	(5.049)	(7.948)	(9.014)	(4.807)	(3.701)
HPI x S [b]	11.94*	6.957*	1.608	-4.624*	-6.280**
	(6.985)	(3.889)	(2.674)	(2.519)	(2.971)
HPI x BC [b]	1.069***	0.649*	-0.0960	-0.0355	-0.0512
	(0.391)	(0.346)	(0.271)	(0.144)	(0.180)
State by Year FE	561	561	561	561	561
Household Head Occupation FE	338	338	338	338	338
Observations	311,226	980,508	1,505,778	1,666,668	1,037,849
R-squared	0.063	0.069	0.056	0.047	0.037
Mean HEL/HELOC	8.39%	15.20%	17.83%	16.45%	11.82%
Mean Percent HPI Increase	0.207	0.365	0.602	0.814	0.936
Mean UR	0.051	0.036	0.032	0.031	0.034
Mean S	0.023	0.021	0.021	0.021	0.022
Mean BC	0.400	0.407	0.402	0.388	0.369

[a] One * indicates significant at 10% level, ** at 5%, *** at 1%. All models also include household head attributes.
[b] Measures are calculated by regressing unemployment status on month fixed effects, quarterly percent change in GDP, education, age, age squared, and gender using CPS 1993-2002 data for each occupation. Seasonality is the difference between the largest and smallest monthly fixed effect estimate. Business cycle effect is the absolute value of the coefficient estimate for quarterly percent change in GDP.

Table 4.5
Comparison of household heads in low versus high unemployment rate occupations [a]
(standard errors clustered at state level in parenthesis)

Dependent variable = 100 if hold a HEL or HELOC; 0 otherwise.

Panel A – Low Unemployment Rate Occupations (UR ≤ 5%)

	Age group year range (by Household Head Age)				
	20-29	30-39	40-49	50-59	60-69
Estimated Max. % HPI Increase Since Moved In (HPI)	10.28***	9.119***	6.042***	3.979***	3.107***
	(1.933)	(1.836)	(1.513)	(1.181)	(1.089)
Avg. UR for Age and Occ. Group 1993-2002 (UR)	-15.14*	-54.55***	-44.79***	-26.85***	-13.93***
	(7.650)	(8.435)	(5.121)	(4.889)	(3.052)
Seasonality in Occupation-Specific UR (S): [b]	-24.42***	-11.62**	-14.08***	-20.48***	-12.20***
High – Low Monthly Factor	(7.526)	(5.136)	(2.041)	(2.609)	(3.639)
Business Cycle Effect on Occ.-Specific UR (BC): [b]	0.838***	0.871***	0.599***	0.915***	0.316***
Impact of Quarterly % Change in GDP	(0.241)	(0.177)	(0.0976)	(0.116)	(0.115)
State by Year FE	561	561	561	561	561
Household Head Broad Occupation Group FE	17	17	17	17	17
Observations	191,487	769,599	1,311,183	1,467,149	887,611
R-squared	0.067	0.067	0.052	0.044	0.035
Mean HEL/HELOC	9.30%	16.40%	18.61%	16.92%	12.04%
Mean Percent HPI Increase	0.193	0.355	0.599	0.812	0.934
Mean UR	0.028	0.023	0.025	0.025	0.028
Mean S	0.014	0.014	0.016	0.016	0.017
Mean BC	0.402	0.404	0.399	0.368	0.322

Panel B – High Unemployment Rate Occupations (UR > 5%)

	Age group year range (by Household Head Age)				
	20-29	30-39	40-49	50-59	60-69
Estimated Max. % HPI Increase Since Moved In (HPI)	6.301***	5.084***	3.607***	3.282***	2.122**
	(1.162)	(1.154)	(1.270)	(1.139)	(1.004)
Avg. UR for Age and Occ. Group 1993-2002 (UR)	-4.775	-6.392**	-1.871	-4.106	2.176
	(3.313)	(3.170)	(4.377)	(3.494)	(3.641)
Seasonality in Occupation-Specific UR (S): [b]	7.340**	8.974***	6.007**	6.188**	0.750
High – Low Monthly Factor	(3.040)	(3.275)	(2.746)	(2.812)	(3.285)
Business Cycle Effect on Occ.-Specific UR (BC): [b]	0.168	-0.0809	-0.283	-0.251*	-0.226
Impact of Quarterly % Change in GDP	(0.207)	(0.186)	(0.170)	(0.145)	(0.136)
State by Year FE	561	561	561	561	561
Household Head Broad Occupation Group FE	17	17	17	17	17
Observations	119,739	210,909	194,595	199,519	150,238
R-squared	0.051	0.058	0.054	0.045	0.038
Mean HEL/HELOC	6.98%	11.01%	12.67%	12.92%	10.49%
Mean Percent HPI Increase	0.229	0.398	0.628	0.826	0.948
Mean UR	0.087	0.079	0.078	0.074	0.073
Mean S	0.036	0.043	0.056	0.061	0.050
Mean BC	0.397	0.418	0.425	0.542	0.651

[a] One * indicates significant at 10% level, ** at 5%, *** at 1%. All models also include household head attributes.
[b] Measures are calculated by regressing unemployment status on month fixed effects, quarterly percent change in GDP, education, age, age squared, and gender using CPS 1993-2002 data for each occupation. Seasonality is the difference between the largest and smallest monthly fixed effect estimate. Business cycle effect is the absolute value of the coefficient estimate for quarterly percent change in GDP.

Table 4.6A
Interacted model for household heads in low unemployment rate occupations (UR ≤ 5%)[a]
(standard errors clustered at state level in parenthesis)

Dependent variable = 100 if hold a HEL or HELOC; 0 otherwise.					
	Age group year range (by Household Head Age)				
	20-29	30-39	40-49	50-59	60-69
Estimated Max. % HPI Increase Since Moved In (HPI)	11.41***	9.933***	6.720***	4.290***	3.642***
	(2.476)	(1.904)	(1.626)	(1.269)	(1.161)
Avg. UR for Age and Occ. Group 1993-2002 (UR)	-4.839	-34.83***	-27.61**	-18.27**	1.744
	(7.949)	(11.03)	(11.34)	(7.505)	(5.501)
Seasonality in Occupation-Specific UR (S): [b]	-24.71***	-15.44**	-14.35***	-14.30***	-6.922*
High – Low Monthly Factor	(7.740)	(6.153)	(4.642)	(5.068)	(3.928)
Business Cycle Effect on Occ.-Specific UR (BC): [b]	0.633***	0.593***	0.564***	0.769***	0.278
Impact of Quarterly % Change in GDP	(0.220)	(0.196)	(0.182)	(0.249)	(0.236)
Interactions					
HPI x UR	-55.64***	-54.47***	-28.15*	-10.44	-16.83***
	(20.39)	(18.68)	(15.87)	(10.75)	(5.112)
HPI x S	0.866	9.383	0.384	-7.212	-5.564
	(24.67)	(10.26)	(6.035)	(4.785)	(5.407)
HPI x BC	1.112**	0.784*	0.0475	0.176	0.0380
	(0.546)	(0.403)	(0.282)	(0.245)	(0.233)
State by Year FE	561	561	561	561	561
Household Head Broad Occupation Group FE	17	17	17	17	17
Observations	191,487	769,599	1,311,183	1,467,149	887,611
R-squared	0.067	0.067	0.052	0.044	0.035
Mean HEL/HELOC	9.30%	16.40%	18.61%	16.92%	12.04%
Mean Percent HPI Increase	0.193	0.355	0.599	0.812	0.934
Mean UR	0.028	0.023	0.025	0.025	0.028
Mean S	0.014	0.014	0.016	0.016	0.017
Mean BC	0.402	0.404	0.399	0.368	0.322

[a] One * indicates significant at 10% level, ** at 5%, *** at 1%. All models also include household head attributes.

[b] Measures are calculated by regressing unemployment status on month fixed effects, quarterly percent change in GDP, education, age, age squared, and gender using CPS 1993-2002 data for each occupation. Seasonality is the difference between the largest and smallest monthly fixed effect estimate. Business cycle effect is the absolute value of the coefficient estimate for quarterly percent change in GDP.

Table 4.6B
Interacted model for household heads in high unemployment rate occupations (UR > 5%)[a]
(standard errors clustered at state level in parenthesis)

Dependent variable = 100 if hold a HEL or HELOC; 0 otherwise.					
	Age group year range (by Household Head Age)				
	20-29	30-39	40-49	50-59	60-69
Estimated Max. % HPI Increase Since Moved In (HPI)	8.454***	6.727***	3.906**	3.394***	2.838***
	(1.246)	(1.372)	(1.541)	(1.147)	(1.057)
Avg. UR for Age and Occ. Group 1993-2002 (UR)	3.008	2.106	-3.028	-6.612	4.997
	(3.632)	(5.633)	(6.766)	(5.336)	(6.602)
Seasonality in Occupation-Specific UR (S): [b]	4.277	8.486**	7.979**	8.184**	8.693**
High – Low Monthly Factor	(3.098)	(3.486)	(3.201)	(3.633)	(3.855)
Business Cycle Effect on Occ.-Specific UR (BC): [b]	-0.0513	-0.0444	0.197	0.0842	-0.0486
Impact of Quarterly % Change in GDP	(0.214)	(0.239)	(0.335)	(0.231)	(0.277)
Interactions					
HPI x UR	-34.33***	-21.16*	1.929	3.002	-2.927
	(8.602)	(10.68)	(9.000)	(5.067)	(4.863)
HPI x S	13.06*	1.247	-3.068	-2.295	-8.037**
	(7.683)	(5.684)	(4.382)	(3.438)	(3.513)
HPI x BC	1.047*	-0.0785	-0.738*	-0.393*	-0.175
	(0.578)	(0.431)	(0.423)	(0.232)	(0.243)
State by Year FE	561	561	561	561	561
Household Head Broad Occupation Group FE	17	17	17	17	17
Observations	119,739	210,909	194,595	199,519	150,238
R-squared	0.051	0.058	0.054	0.045	0.038
Mean HEL/HELOC	6.98%	11.01%	12.67%	12.92%	10.49%
Mean Percent HPI Increase	0.229	0.398	0.628	0.826	0.948
Mean UR	0.087	0.079	0.078	0.074	0.073
Mean S	0.036	0.043	0.056	0.061	0.050
Mean BC	0.397	0.418	0.425	0.542	0.651

[a] One * indicates significant at 10% level, ** at 5%, *** at 1%. All models also include household head attributes.

[b] Measures are calculated by regressing unemployment status on month fixed effects, quarterly percent change in GDP, education, age, age squared, and gender using CPS 1993-2002 data for each occupation. Seasonality is the difference between the largest and smallest monthly fixed effect estimate. Business cycle effect is the absolute value of the coefficient estimate for quarterly percent change in GDP.

Table 4.7
Comparison of two-worker households by degree of spousal correlation in unemployment rate [a]
(standard errors clustered at state level in parenthesis)

Dependent variable = 100 if hold a HEL or HELOC; 0 otherwise.

Panel A – Negative or Zero Correlation
(-1.0 ≤ Spousal UR Correlation Coefficient ≤ 0) [c]

	Age group year range (by Household Head Age)				
	20-29	30-39	40-49	50-59	60-69
Estimated Max. % HPI Increase Since Moved In (HPI)	16.16***	9.726***	7.363***	3.901***	4.185***
	(2.794)	(1.805)	(1.737)	(1.062)	(1.488)
Avg. UR for Age and Occ. Group 1993-2002 (UR)	-15.66	-26.33***	-1.924	12.26	8.302
	(9.512)	(8.602)	(9.452)	(9.412)	(6.315)
Seasonality in Occupation-Specific UR (S): [b]	-15.84	6.276	-7.499	-11.97*	-20.49***
High – Low Monthly Factor	(10.30)	(6.557)	(7.078)	(6.204)	(5.926)
Business Cycle Effect on Occ.-Specific UR (BC): [b]	1.126**	-0.325	0.0555	-0.210	-0.0786
Impact of Quarterly % Change in GDP	(0.537)	(0.281)	(0.331)	(0.268)	(0.310)
State by Year FE	561	561	561	561	561
Household Head & Spouse Broad Occ. Group FE	34	34	34	34	34
Observations	21,055	79,858	102,973	102,248	50,968
R-squared	0.101	0.073	0.054	0.047	0.051
Mean HEL/HELOC	10.31%	17.65%	21.01%	19.79%	14.58%
Mean Percent HPI Increase	0.179	0.343	0.603	0.843	0.961
Mean UR	0.040	0.029	0.027	0.027	0.033
Mean S	0.021	0.020	0.021	0.022	0.024
Mean BC	0.463	0.469	0.480	0.467	0.462

Panel B – Moderate Positive Correlation
(0 < Spousal UR Correlation Coefficient ≤ 0.5) [c]

	Age group year range (by Household Head Age)				
	20-29	30-39	40-49	50-59	60-69
Estimated Max. % HPI Increase Since Moved In (HPI)	12.50***	9.851***	7.203***	4.795***	3.887***
	(1.886)	(2.044)	(1.726)	(1.459)	(1.342)
Avg. UR for Age and Occ. Group 1993-2002 (UR)	-8.366	-24.71***	-23.96***	-4.350	0.0648
	(5.782)	(4.617)	(5.085)	(4.323)	(4.870)
Seasonality in Occupation-Specific UR (S): [b]	-0.963	0.531	-6.295	-14.39***	-12.65***
High – Low Monthly Factor	(6.785)	(4.700)	(3.891)	(3.619)	(3.432)
Business Cycle Effect on Occ.-Specific UR (BC): [b]	0.365	0.365	0.131	0.315	-0.188
Impact of Quarterly % Change in GDP	(0.298)	(0.219)	(0.194)	(0.232)	(0.187)
State by Year FE	561	561	561	561	561
Household Head & Spouse Broad Occ. Group FE	34	34	34	34	34
Observations	64,062	239,868	345,652	362,650	183,678
R-squared	0.076	0.070	0.053	0.047	0.042
Mean HEL/HELOC	9.87%	17.43%	20.92%	19.62%	14.43%
Mean Percent HPI Increase	0.185	0.360	0.615	0.844	0.952
Mean UR	0.045	0.032	0.029	0.029	0.033
Mean S	0.022	0.021	0.021	0.022	0.023
Mean BC	0.390	0.396	0.405	0.397	0.385

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Table 4.7 (Cont.)
Comparison of two-worker households by degree of spousal correlation in unemployment rate [a]
(standard errors clustered at state level in parenthesis)

Dependent variable = 100 if hold a HEL or HELOC; 0 otherwise.

Panel C – Strong Positive Correlation
(0.5 < Spousal UR Correlation Coefficient ≤ 1.0) [c]

	Age group year range (by Household Head Age)				
	20-29	30-39	40-49	50-59	60-69
Estimated Max. % HPI Increase Since Moved In (HPI)	11.18***	9.506***	6.030***	4.410***	3.456***
	(2.673)	(1.860)	(1.659)	(1.224)	(1.099)
Avg. UR for Age and Occ. Group 1993-2002 (UR)	-11.49*	-27.66***	-23.34***	-16.10***	-8.186*
	(5.776)	(5.502)	(5.209)	(4.924)	(4.623)
Seasonality in Occupation-Specific UR (S): [b]	8.356**	10.11**	2.217	-3.179	-4.490*
High – Low Monthly Factor	(3.700)	(4.340)	(3.601)	(2.785)	(2.560)
Business Cycle Effect on Occ.-Specific UR (BC): [b]	0.187	0.333	0.347	0.590***	0.644**
Impact of Quarterly % Change in GDP	(0.307)	(0.238)	(0.217)	(0.199)	(0.253)
State by Year FE	561	561	561	561	561
Household Head & Spouse Broad Occ. Group FE	34	34	34	34	34
Observations	82,576	316,796	476,376	493,905	256,590
R-squared	0.074	0.069	0.054	0.046	0.041
Mean HEL/HELOC	9.98%	17.22%	19.99%	18.76%	13.93%
Mean Percent HPI Increase	0.196	0.366	0.615	0.831	0.945
Mean UR	0.054	0.038	0.034	0.033	0.035
Mean S	0.022	0.020	0.021	0.021	0.022
Mean BC	0.381	0.394	0.382	0.368	0.345

[a] One * indicates significant at 10% level, ** at 5%, *** at 1%. All models also include household head and spouse attributes.
[b] Measures are calculated by regressing unemployment status on month fixed effects, quarterly percent change in GDP, education, age, age squared, and gender using CPS 1993-2002 data for each occupation. Seasonality is the difference between the largest and smallest monthly fixed effect estimate. Business cycle effect is the absolute value of the coefficient estimate for quarterly percent change in GDP.
[c] Correlation coefficient calculated using yearly occupation-specific unemployment rates estimated with CPS 1993-2002 data.

Table 4.8
Interacted model for two-worker households with a strong positive spousal correlation in unemployment rate (0.5 < Spousal UR Correlation Coefficient ≤ 1.0) [a]
(standard errors clustered at state level in parenthesis)

Dependent variable = 100 if hold a HEL or HELOC; 0 otherwise.

	Age group year range (by Household Head Age)				
	20-29	30-39	40-49	50-59	60-69
Estimated Max. % HPI Increase Since Moved In (HPI)	13.32***	11.90***	6.845***	4.955***	4.175***
	(2.500)	(1.869)	(1.777)	(1.266)	(1.159)
Avg. UR for Age and Occ. Group 1993-2002 (UR)	2.542	-0.117	-4.482	-2.093	4.713
	(6.167)	(6.716)	(10.16)	(8.879)	(8.034)
Seasonality in Occupation-Specific UR (S): [b]	3.269	4.511	-3.872	0.663	2.707
High – Low Monthly Factor	(4.137)	(4.810)	(5.858)	(5.409)	(5.324)
Business Cycle Effect on Occ.-Specific UR (BC): [b]	-0.443	0.375	0.356	0.438	0.961**
Impact of Quarterly % Change in GDP	(0.320)	(0.288)	(0.347)	(0.386)	(0.376)
Interactions					
HPI x UR	-73.11***	-71.00***	-29.44**	-16.29*	-13.20
	(18.35)	(10.77)	(13.47)	(9.242)	(8.177)
HPI x S	25.89	14.68**	9.575	-4.221	-7.404
	(18.75)	(6.371)	(7.140)	(5.928)	(4.900)
HPI x BC	3.236***	-0.168	-0.0294	0.175	-0.340
	(1.201)	(0.590)	(0.584)	(0.307)	(0.324)
State by Year FE	561	561	561	561	561
Household Head & Spouse Broad Occ. Group FE	34	34	34	34	34
Observations	82,576	316,796	476,376	493,905	256,590
R-squared	0.074	0.070	0.054	0.046	0.041
Mean HEL/HELOC	9.98%	17.22%	19.99%	18.76%	13.93%
Mean Percent HPI Increase	0.196	0.366	0.615	0.831	0.945
Mean UR	0.054	0.038	0.034	0.033	0.035
Mean S	0.022	0.020	0.021	0.021	0.022
Mean BC	0.381	0.394	0.382	0.368	0.345

[a] One * indicates significant at 10% level, ** at 5%, *** at 1%. All models also include household head and spouse attributes. Correlation coefficient calculated using yearly occupation-specific unemployment rates estimated with CPS 1993-2002 data.
[b] Measures are calculated by regressing unemployment status on month fixed effects, quarterly percent change in GDP, education, age, age squared, and gender using CPS 1993-2002 data for each occupation. Seasonality is the difference between the largest and smallest monthly fixed effect estimate. Business cycle effect is the absolute value of the coefficient estimate for quarterly percent change in GDP.

5. APPENDIX

5.1 Appendix to Chapter 2

Table A2-1
Policy effect for married women who moved into their current residence 5 or more years ago
(Standard errors clustered at the state by year level in parentheses)[a]

Panel A: Baseline Model

		Closest to NJ………..>….....…>….….….>……….Furthest from NJ				
		NYC and PHL MSAs		DE, NY, and PA[b]		
	New Jersey (1)	NJ Border PUMAs (2)	Non-NJ Border PUMAs (3)	< 60 miles from NJ (4)	> 60 miles from NJ (5)	All Other States (6)
Currently Eligible: Post 2009 x child under age1	0.0538** (0.0255)	0.0572 (0.0372)	0.0869*** (0.0267)	0.0447 (0.0474)	0.0251 (0.0217)	0.0364*** (0.00553)
Col(1) - Col(X) Coef. [c]	-	[-0.003]	[-0.033]	[0.009]	[0.029]	[0.017]
Eligible 1-3 years ago: Post 2009 x qualifying age[d]	0.0534*** (0.0194)	0.0256 (0.0223)	0.0416** (0.0176)	0.0120 (0.0296)	0.0196 (0.0149)	0.0193*** (0.00361)
Col(1) - Col(X) Coef. [c]	-	[0.028]	[0.012]	[0.041]	[0.034*]	[0.034**]
State by Year F.E.	8	16	16	24	16	368
Observations	16,210	7,448	16,386	7,198	28,718	417,536
R-squared	0.055	0.093	0.105	0.089	0.078	0.084
Employment Rate	66.9%	66.4%	60.9%	72.2%	74.1%	71.5%

Panel B: Persistence of Effects

		Closest to NJ………..>….....…>….….….>……….Furthest from NJ				
		NYC and PHL MSAs		DE, NY, and PA[b]		
	New Jersey (1)	NJ Border PUMAs (2)	Non-NJ Border PUMAs (3)	< 60 miles from NJ (4)	> 60 miles from NJ (5)	All Other States (6)
Post 2009 x Child under age 1	0.0541** (0.0255)	0.0575 (0.0372)	0.0868*** (0.0267)	0.0449 (0.0474)	0.0248 (0.0217)	0.0365*** (0.00552)
Col(1) - Col(X) Coef.[c]	-	[-0.003]	[-0.033]	[0.009]	[0.029]	[0.018]
Post 2010 x Youngest child age 1	0.0551** (0.0262)	0.0326 (0.0341)	0.0378 (0.0252)	0.0341 (0.0428)	-0.00115 (0.0212)	0.0239*** (0.00521)
Col(1) - Col(X) Coef.[c]	-	[0.023]	[0.017]	[0.021]	[0.056*]	[0.031]
Post 2011 x Youngest child age 2	0.0764** (0.0312)	0.0458 (0.0370)	0.0388 (0.0262)	-0.0287 (0.0446)	0.0277 (0.0211)	0.0207*** (0.00577)
Col(1) - Col(X) Coef.[c]	-	[0.031]	[0.038]	[0.105**]	[0.049*]	[0.056**]
Post 2012 x Youngest child age 3	0.00673 (0.0333)	-0.0352 (0.0545)	0.0550 (0.0358)	0.0430 (0.0586)	0.0566** (0.0259)	0.0055 (0.00783)
Col(1) - Col(X) Coef.[c]	-	[0.042]	[-0.048]	[-0.036]	[-0.050]	[0.001]
State by Year F.E.	8	16	16	24	16	368
Observations	16,210	7,448	16,386	7,198	28,718	417,536
R-squared	0.055	0.093	0.105	0.089	0.078	0.084
Employment Rate	66.9%	66.4%	60.9%	72.2%	74.1%	71.5%

[a] One * indicates significant at the 10 percent level; ** at 5 % level; *** at 1 % level. All models also include own attributes (education, race, age); spouse education level and youngest child age indicators.
[b] Does not include individuals in these three states residing in the New York and Philadelphia MSAs.
[c] One-sided test of NJ coefficient larger than coefficient from other sample shown in [square brackets].

Table A2-2
Comparison of employment outcomes by age group for women aged 18 to 60
(Standard errors clustered at the state by year level in parentheses)[a]

Panel A: Married women

		Closest to NJ………..>…....…>….…….>……….Furthest from NJ				
		NYC and PHL MSAs		DE, NY, and PA[b]		
	New Jersey	NJ Border PUMAs	Non-NJ Border PUMAs	< 60 miles from NJ	> 60 miles from NJ	All Other States
	(1)	(2)	(3)	(4)	(5)	(6)
Young (Aged 18 to 40)	-0.0660***	-0.0380***	-0.0530***	-0.0748***	-0.0585***	-0.0563***
	(0.00720)	(0.0113)	(0.00699)	(0.00852)	(0.00528)	(0.00142)
Post 2009	0.0110	0.0114	0.0383***	0.0235	-0.0111	-0.0336***
	(0.00773)	(0.0103)	(0.00449)	(0.0362)	(0.00796)	(0.01152)
Post 2009 x Young	0.0117*	0.00425	0.00424	0.0112	-0.00871*	-0.0043***
	(0.00605)	(0.00815)	(0.00585)	(0.00776)	(0.00479)	(0.00127)
Col(1) - Col(X) Coef.[c]	-	[0.007]	[0.007]	[-0.001]	[0.020***]	[0.016***]
State by Year F.E.	8	16	16	24	16	368
Observations	114,969	111,510	102,244	46,263	193,574	2,950,041
R-squared	0.034	0.045	0.058	0.052	0.058	0.061
Employment Rates:						
Young (aged 18 to 40)	65.4%	66.3%	61.4%	69.8%	70.6%	66.6%
Old (aged 41 to 60)	70.2%	68.9%	67.8%	72.5%	72.4%	69.1%

Panel B: Women married to spouses with BA degree or higher education level

		Closest to NJ………..>…....…>….…….>……….Furthest from NJ				
		NYC and PHL MSAs		DE, NY, and PA[b]		
	New Jersey	NJ Border PUMAs	Non-NJ Border PUMAs	< 60 miles from NJ	> 60 miles from NJ	All Other States
	(1)	(2)	(3)	(4)	(5)	(6)
Young (Aged 18 to 40)	-0.0853***	-0.0536***	-0.0617***	-0.0957***	-0.0946***	-0.0940***
	(0.0108)	(0.0154)	(0.00947)	(0.0178)	(0.00969)	(0.00234)
Post 2009	-0.00749	0.0359***	0.0639**	0.0637*	-0.00376	0.000131
	(0.0106)	(0.0131)	(0.0296)	(0.0357)	(0.0116)	(21.4)
Post 2009 x Young	0.0340***	0.0125	0.0202**	0.00397	0.0260***	0.0192***
	(0.00813)	(0.0132)	(0.00863)	(0.0158)	(0.00904)	(0.00196)
Col(1) - Col(X) Coef.[c]	-	[0.022*]	[0.014]	[0.030**]	[0.008]	[0.015**]
State by Year F.E.	8	16	16	24	16	368
Observations	51,093	49,960	39,439	46,263	54,921	945,789
R-squared	0.020	0.026	0.032	0.052	0.024	0.027
Employment Rates:						
Young (aged 18 to 40)	63.9%	68.3%	65.4%	70.6%	72.4%	68.8%
Old (aged 41 to 60)	70.0%	71.1%	69.2%	73.5%	72.3%	69.7%

[a] One * indicates significant at the 10 percent level; ** at 5 % level; *** at 1 % level. All models also include own attributes (education, race, age); spouse education level indicators.
[b] Does not include individuals in these three states residing in the New York and Philadelphia MSAs.
[c] One-sided test of NJ coefficient larger than coefficient from other sample shown in [square brackets].

5.2 Appendix to Chapter 3

Table A3-1: $5,000 Income cutoff (2013 dollars) when defining work
Unrestricted peer effect model instrumenting for neighbor work status with MSA-level employment rates[a]
(standard errors clustered at the neighborhood level in parentheses)

PANEL A –MEN

Peer Group Definition	Gender	Child	Gen-Educ	Gen-Child	Gen Mar-Child	Gen Ed-Child	Gen-Mar Ed-Child
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
N working peer (WP)	-0.00977	0.00340	0.00508	-0.00442	-0.00481	-0.00128	0.00148
	(0.0122)	(0.0104)	(0.0118)	(0.0101)	(0.0103)	(0.0118)	(0.0125)
N working non-peer (WNP)	0.00293	-0.00353	-0.00498	-0.00452	-0.00716	-0.00213	-0.00404
	(0.0212)	(0.00964)	(0.0147)	(0.0133)	(0.0118)	(0.0130)	(0.0117)
N non-working non-peer (NWNP)	-0.00976	0.00298	-0.00784	-0.00117	0.00285	-0.00652	-0.00225
	(0.0208)	(0.0138)	(0.0168)	(0.0152)	(0.0135)	(0.0156)	(0.0141)
N non-working peer (NWP)	0.00960	-0.0165	-0.0136	-0.0151	-0.0196	0.00352	-0.0211
	(0.0446)	(0.0234)	(0.0477)	(0.0341)	(0.0388)	(0.0468)	(0.0587)
Person Fixed Effects	2,272	2,272	2,272	2,272	2,272	2,272	2,272
% Neighbors that are Peers	34.4%	40.3%	18.9%	19.2%	15.2%	10.8%	8.7%
Mean WP	4.2	4.2	2.4	2.3	1.9	1.4	1.1
Mean WNP	4.0	4.2	6.2	6.3	6.8	7.3	7.6
Mean NWNP	4.1	3.1	5.2	5.1	5.4	5.7	5.8
Mean NWP	1.0	1.8	0.5	0.6	0.4	0.3	0.2
R-square	0.586	0.586	0.586	0.586	0.586	0.586	0.587
Observations	5,409	5,409	5,409	5,409	5,409	5,409	5,400

PANEL B –WOMEN

Peer Group Definition	Gender	Child	Gen-Educ	Gen-Child	Gen Mar-Child	Gen Ed-Child	Gen-Mar Ed-Child
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
N working peer (WP)	0.0378	0.0217	0.0138	0.0410**	0.0226	0.0298	0.0101
	(0.0244)	(0.0141)	(0.0154)	(0.0184)	(0.0186)	(0.0191)	(0.0208)
N working non-peer (WNP)	0.000245	0.00389	0.00449	0.00670	-0.00741	-0.00115	-0.00905
	(0.0182)	(0.0136)	(0.0171)	(0.0146)	(0.0142)	(0.0145)	(0.0133)
N non-working non-peer (NWNP)	-0.0220	0.000829	-0.0103	-0.00559	0.0116	0.00343	0.0131
	(0.0317)	(0.0178)	(0.0227)	(0.0207)	(0.0194)	(0.0186)	(0.0163)
N non-working peer (NWP)	-0.0487	-0.0524*	-0.0287	-0.0667**	-0.0519**	-0.0507*	-0.0303
	(0.0376)	(0.0294)	(0.0259)	(0.0270)	(0.0241)	(0.0283)	(0.0298)
Person Fixed Effects	2,608	2,608	2,608	2,608	2,608	2,608	2,608
% Neighbors that are Peers	39.0%	40.2%	21.3%	21.8%	15.3%	12.0%	8.6%
Mean WP	3.6	4.2	2.0	1.9	1.4	1.1	0.8
Mean WNP	4.7	4.1	6.3	6.4	7.0	7.3	7.6
Mean NWNP	2.2	1.8	1.1	1.2	0.9	0.7	0.5
Mean NWP	2.3	3.0	4.4	4.2	4.9	5.3	5.6
R-square	0.709	0.709	0.709	0.709	0.709	0.709	0.709
Observations	6,252	6,252	6,252	6,252	6,252	6,252	6,252

[a] Sample includes only individuals age 25-60 in two consecutive surveys. One * indicates significant at the 10 percent level; two at 5 % level; three at 1 % level. All models also include: year fixed effects; MSA employment rate; individual education (less than HS; HS and some col.; and BA degree or more); child presence in HH; and marital status. As well as percent of neighbors aged 25 to 60 and their average: education (same 3 categories); marital status; and child in HH.

Table A3-2a: Linear probability model of locating in the same neighborhood cluster controlling for person attributes and residuals from Table 5a[a] (Robust standard errors in parentheses)

PANEL A – MEN

	Gender	Child	Gen-Educ	Gen-Child	Gen Mar-Child	Gen Ed-Child	Gen-Mar Ed-Child
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
*Dif*_HS degree/some college	-0.000228***	-0.000228***	-0.000228***	-0.000228***	-0.000228***	-0.000228***	-0.000228***
	(4.04e-05)	(4.04e-05)	(4.04e-05)	(4.04e-05)	(4.04e-05)	(4.04e-05)	(4.05e-05)
*Dif*_BA degree or more	-0.000724***	-0.000724***	-0.000724***	-0.000724***	-0.000724***	-0.000724***	-0.000722***
	(3.94e-05)	(3.94e-05)	(3.94e-05)	(3.94e-05)	(3.94e-05)	(3.94e-05)	(3.95e-05)
*Dif*_Married	-0.000817***	-0.000817***	-0.000817***	-0.000817***	-0.000817***	-0.000817***	-0.000822***
	(3.75e-05)	(3.75e-05)	(3.75e-05)	(3.75e-05)	(3.75e-05)	(3.75e-05)	(3.76e-05)
*Dif*_Child under age 18	-0.000190***	-0.000190***	-0.000190***	-0.000190***	-0.000190***	-0.000190***	-0.000187***
	(3.81e-05)	(3.81e-05)	(3.81e-05)	(3.81e-05)	(3.81e-05)	(3.81e-05)	(3.82e-05)
*Dif*_1st Stage Residuals	-0.000209**	-0.000198**	-0.000206**	-0.000208**	-0.000207**	-0.000204**	-0.000207**
	(8.29e-05)	(8.29e-05)	(8.30e-05)	(8.29e-05)	(8.30e-05)	(8.28e-05)	(8.31e-05)
Constant	0.00262***	0.00262***	0.00262***	0.00262***	0.00262***	0.00262***	0.00262***
	(4.22e-05)	(4.22e-05)	(4.22e-05)	(4.22e-05)	(4.22e-05)	(4.22e-05)	(4.23e-05)
Observations	5,033,350	5,033,350	5,033,350	5,033,350	5,033,350	5,033,350	5,016,312

PANEL B – WOMEN

	Gender	Child	Gen-Educ	Gen-Child	Gen Mar-Child	Gen Ed-Child	Gen-Mar Ed-Child
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
*Dif*_HS degree/some college	-0.000191***	-0.000191***	-0.000191***	-0.000191***	-0.000191***	-0.000191***	-0.000191***
	(3.34e-05)	(3.34e-05)	(3.34e-05)	(3.34e-05)	(3.34e-05)	(3.34e-05)	(3.34e-05)
*Dif*_BA degree or more	-0.000360***	-0.000359***	-0.000359***	-0.000359***	-0.000359***	-0.000359***	-0.000359***
	(3.32e-05)	(3.32e-05)	(3.32e-05)	(3.32e-05)	(3.32e-05)	(3.32e-05)	(3.32e-05)
*Dif*_Married	-0.000853***	-0.000852***	-0.000852***	-0.000852***	-0.000852***	-0.000852***	-0.000852***
	(3.09e-05)	(3.09e-05)	(3.09e-05)	(3.09e-05)	(3.09e-05)	(3.09e-05)	(3.09e-05)
*Dif*_Child under age 18	-0.000243***	-0.000243***	-0.000243***	-0.000243***	-0.000243***	-0.000243***	-0.000243***
	(3.19e-05)	(3.19e-05)	(3.19e-05)	(3.19e-05)	(3.19e-05)	(3.19e-05)	(3.19e-05)
*Dif*_1st Stage Residuals	-0.000070	-0.000051	-0.000055	-0.000061	-0.000055	-0.000057	-0.000052
	(6.10e-05)	(6.06e-05)	(6.07e-05)	(6.09e-05)	(6.07e-05)	(6.10e-05)	(6.07e-05)
Constant	0.00239***	0.00238***	0.00239***	0.00239***	0.00239***	0.00239***	0.00238***
	(3.68e-05)	(3.68e-05)	(3.68e-05)	(3.69e-05)	(3.68e-05)	(3.69e-05)	(3.68e-05)
Observations	6,692,941	6,692,941	6,692,941	6,692,941	6,692,941	6,692,941	6,692,941

[a] One * indicates significant at the 10 percent level; two at 5 % level; three at 1 % level.

Table A3-2b: Linear probability model of locating in the same neighborhood cluster controlling for person attributes and residuals from Table 5b[a]
(Robust standard errors in parentheses)

PANEL A – MEN

	Gender	Child	Gen-Educ	Gen-Child	Gen Mar-Child	Gen Ed-Child	Gen-Mar Ed-Child
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
*Dif*_HS degree/some college	-0.000228***	-0.000228***	-0.000228***	-0.000228***	-0.000228***	-0.000228***	-0.000228***
	(4.04e-05)	(4.04e-05)	(4.04e-05)	(4.04e-05)	(4.04e-05)	(4.04e-05)	(4.05e-05)
*Dif*_BA degree or more	-0.000724***	-0.000724***	-0.000724***	-0.000724***	-0.000724***	-0.000724***	-0.000722***
	(3.94e-05)	(3.94e-05)	(3.94e-05)	(3.94e-05)	(3.94e-05)	(3.94e-05)	(3.95e-05)
*Dif*_Married	-0.000817***	-0.000817***	-0.000817***	-0.000817***	-0.000817***	-0.000817***	-0.000823***
	(3.75e-05)	(3.75e-05)	(3.75e-05)	(3.75e-05)	(3.75e-05)	(3.75e-05)	(3.76e-05)
*Dif*_Child under age 18	-0.000190***	-0.000190***	-0.000190***	-0.000190***	-0.000190***	-0.000190***	-0.000187***
	(3.81e-05)	(3.81e-05)	(3.81e-05)	(3.81e-05)	(3.81e-05)	(3.81e-05)	(3.82e-05)
*Dif*_1[st] Stage Residuals	-0.000209**	-0.000199**	-0.000209**	-0.000211**	-0.000210**	-0.000203**	-0.000209**
	(8.29e-05)	(8.29e-05)	(8.31e-05)	(8.30e-05)	(8.30e-05)	(8.29e-05)	(8.32e-05)
Constant	0.00262***	0.00262***	0.00262***	0.00262***	0.00262***	0.00262***	0.00262***
	(4.22e-05)	(4.22e-05)	(4.23e-05)	(4.22e-05)	(4.23e-05)	(4.22e-05)	(4.23e-05)
Observations	5,033,350	5,033,350	5,033,350	5,033,350	5,033,350	5,033,350	5,016,312

PANEL B – WOMEN

	Gender	Child	Gen-Educ	Gen-Child	Gen Mar-Child	Gen Ed-Child	Gen-Mar Ed-Child
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
*Dif*_HS degree/some college	-0.000191***	-0.000191***	-0.000191***	-0.000191***	-0.000191***	-0.000191***	-0.000191***
	(3.34e-05)	(3.34e-05)	(3.34e-05)	(3.34e-05)	(3.34e-05)	(3.34e-05)	(3.34e-05)
*Dif*_BA degree or more	-0.000360***	-0.000359***	-0.000359***	-0.000360***	-0.000360***	-0.000360***	-0.000359***
	(3.32e-05)	(3.32e-05)	(3.32e-05)	(3.32e-05)	(3.32e-05)	(3.32e-05)	(3.32e-05)
*Dif*_Married	-0.000853***	-0.000852***	-0.000852***	-0.000853***	-0.000853***	-0.000853***	-0.000852***
	(3.09e-05)	(3.09e-05)	(3.09e-05)	(3.09e-05)	(3.09e-05)	(3.09e-05)	(3.09e-05)
*Dif*_Child under age 18	-0.000243***	-0.000243***	-0.000243***	-0.000243***	-0.000243***	-0.000243***	-0.000243***
	(3.19e-05)	(3.19e-05)	(3.19e-05)	(3.19e-05)	(3.19e-05)	(3.19e-05)	(3.19e-05)
*Dif*_1[st] Stage Residuals	-0.000075	-0.000065	-0.000060	-0.000082	-0.000068	-0.000073	-0.000059
	(6.11e-05)	(6.12e-05)	(6.10e-05)	(6.16e-05)	(6.11e-05)	(6.15e-05)	(6.10e-05)
Constant	0.00239***	0.00239***	0.00239***	0.00239***	0.00239***	0.00239***	0.00239***
	(3.69e-05)	(3.69e-05)	(3.69e-05)	(3.70e-05)	(3.69e-05)	(3.70e-05)	(3.69e-05)
Observations	6,692,941	6,692,941	6,692,941	6,692,941	6,692,941	6,692,941	6,692,941

[a] One * indicates significant at the 10 percent level; two at 5 % level; three at 1 % level.

5.3 Appendix to Chapter 4

Table A4-1
Average unemployment risk measures for broad occupation groups

Broad Occupation Group	Occ. Codes [a]	U. Rate	High – low monthly seasonal factor	Impact of Quarterly % Change in GDP
Managerial & Professional Specialty				
Executive, Administrative, and Managerial	003 to 022	2.13%	0.016	-0.185
Management Related	023 to 037	2.87%	0.024	-0.283
Professional Specialty	043 to 200	2.42%	0.033	-0.032
Technical, Sales, & Administrative Support				
Technicians, and Related Support	203 to 235	2.78%	0.026	-0.323
Sales	243 to 290	4.66%	0.022	0.037
Administrative Support, and Clerical	303 to 391	4.54%	0.030	-0.191
Service				
Private Household	405 to 408	7.85%	0.023	0.437
Protective Service	415 to 427	3.93%	0.060	0.254
Other Service	434 to 469	6.07%	0.035	0.050
Farming, Forestry, & Fishing				
Farm Operators and Managers	473 to 476	1.77%	0.025	0.391
Other Agricultural and Related	479 to 498	10.90%	0.114	0.198
Precision Production, Craft, & Repair				
Mechanics and Repairers	503 to 549	3.57%	0.030	-0.376
Construction Trades	558 to 599	8.34%	0.080	-0.429
Extractive	614 to 617	7.56%	0.079	-0.941
Precision Production	628 to 699	4.75%	0.055	-0.062
Operators, Fabricators, & Laborers				
Machine Operators, Assemblers, and Inspectors	703 to 799	6.98%	0.058	-1.644
Transportation, Material Moving	803 to 890	7.71%	0.062	0.066

[a] Based on 1990 census occupational classification system.

VITA

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